

FINAL REPORT

Post-fire Water Quality: An Investigation of Determinants and Recovery Processes in Burned Watersheds across the Western U.S.

JFSP PROJECT ID: # 14-1-06-14

October 1, 2014 – September 30, 2018

Terri S. Hogue, Professor and Director
Civil and Environmental Engineering Department
Colorado School of Mines

John McCray, Professor
Civil and Environmental Engineering Department
Colorado School of Mines



FIRESCIENCE.GOV
Research Supporting Sound Decisions



The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the opinions or policies of the U.S. Government. Mention of trade names or commercial products does not constitute their endorsement by the U.S. Government.

Abstract

Wildfires are a natural disturbance that are increasing in size and severity in forested landscapes across the Western United States. Forest fires affect water quality in the disrupted watershed, which can significantly alter the aquatic ecosystem, including sensitive trout (*Salmonidae*) and macroinvertebrate species. However, the type and duration of the water quality impact from fire is unpredictable. Previous studies on individual fires have observed an increase in various forms of nutrients, ions, sediments, and metals in stream water for different post-fire time periods. While wildfires clearly are growing in size and severity, less is known about the type of stream water quality and community impacts that should be anticipated from these growing fires.

This study explored water quality response from fire. First, we investigated how water quality and the aquatic community were disrupted by a large Colorado fire. The West Fork Fire Complex consumed 110,000 acres of forest in the state of Colorado during the summer of 2013. The recent fire surrounded the Rio Grande, affecting water quality and habitat critical to insects and fish. The water quality of the Rio Grande (above and below the burn) and some of the effected tributaries was monitored for three years after the fire. All water quality parameters remained the same above and below the fire except turbidity and total suspended solids. Steep, severely burned hillslopes experienced erosion and were the source of sediment loading into the surface water. Despite elevated turbidity levels that persisted for three years in close proximity to the fire, the ecosystem showed resiliency and aquatic macroinvertebrate populations and trout populations have recovered.

To examine how water quality generally impacts water quality, data was compiled for over 24,000 fires across the western United States to evaluate post-fire water quality response. Data from 159 of these fires in 153 burned watersheds were used to identify common water quality response during the first five years after a fire. Within this large dataset, a subset of ten fires was examined further to identify trends in water quality response. Change-point analysis was used to identify moments in the post-fire water quality data where significant shifts in analyte concentrations occurred. Evidence from this analysis reveals significant increases in nutrient flux (different forms of nitrogen and phosphorus), major-ion flux, and metal concentrations are the most common changes in stream water quality within the first five years after fire. Assembling this unique and extensive data set provided the opportunity to determine the most common post-fire water quality changes in the large and diverse Western U.S.

After looking at this large number of fires, the physical determinants driving water quality response and recovery were evaluated. Through the use of the conditional inference tree technique and Spearman correlation analysis, the drivers of post-fire water quality response were exposed. Results show that the geology of the burn area, which influences the soil characteristics, burn severity, and the rate of vegetation recovery are the key determinants of water quality change and resiliency.

Results from this project expand the scientific knowledge of how wildfires impact surface water quality and the communities that depend on it. Through compiling a large dataset, it was possible to identify common post-fire water quality responses and the watershed features that control them. This research also provides critical information on water quality behavior to land and water managers in anticipation of, and following, a wildfire.

TABLE OF CONTENTS

ABSTRACT.....ii

LIST OF TABLESiv

LIST OF FIGURESv

KEYWORDS.....1

ACKNOWLEDGEMENTS1

PROJECT JUSTIFICATION AND EXPECTED BENEFITS.....1

OBJECTIVES.....1

1. WATER QUALITY IMPACTS FROM THE WEST FORK COMPLEX FIRE.....2

2. POST-FIRE WATER QUALITY RESPONSE IN THE WESTERN UNITED STATES.....11

3. EVALUATING THE FACTORS RESPONSIBLE FOR POST-FIRE WATER QUALITY
RESPONSE IN FORESTS OF THE WESTERN USA.....22

CONCLUDING REMARKS AND KEY FINDINGS.....28

IMPLICATIONS FOR MANAGEMENT AND FUTURE RESEARCH.....29

APPENDIX A: CONTACT INFORMATION FOR KEY PROJECT PERSONNEL.....39

APPENDIX B: LIST OF COMPLETED PUBLICATIONS.....40

APPENDIX C: METADATA.....42

LIST OF TABLES

TABLE 1. Water quality, macroinvertebrate, and fish sampling locations above and below the west fork complex fire.....6

TABLE 2. Results from statistical comparison testing among control (thirty mile, squaw, and red mountain) and fire-impacted sites (little squaw, trout, box, marshall park, and wagon wheel gap).....8

TABLE 3. Fish population metrics above and below the landslide in trout creek one year after the landslide and two and three years after the fire.....10

TABLE 4. Summary of average analyte concentration and flux data for all fires.....17

LIST OF FIGURES

FIGURE 1. The Upper Rio Grande watershed in southwestern Colorado.....	4
FIGURE 2. Boxplots showing turbidity levels measured in 2015 (a) and 2016 (b) in the Rio Grande above the fire in blue, Thirty Mile (TM), and below the fire in red at Box Canyon (BC), Marshall Park (MP), Wagon Wheel Gap (WW), the South Fork of the Rio Grande (SF) and Del Norte (DN).....	8
FIGURE 3. The Shannon Diversity Index (SDI) for control and impact sites from before the fire in 2012 and after the fire in 2014-2016.....	9
FIGURE 4. Map of 153 fire-impacted watersheds in the western United States with sufficient pre- and post-fire water quality data used in the analysis.....	13
FIGURE 5. Hydrograph and hyetograph (a), and flat model change-point graphs for total nitrogen (b) with data from the Boise River downstream of the Foothills Fire.....	19
FIGURE 6. Hydrograph and hyetograph (a), and flat change-point model graph (b) for total iron concentrations with data from the Cache La Poudre River downstream of the High Park Fire.....	20
FIGURE 7. Conditional inference tree results illustrating the significant relationship between the percent of organic matter in the burn area soil and the median percent change in dissolved metals concentrations (Al, Ba, Cd, Cu, Mn, Pb, and Zn).....	26
FIGURE 8. Conditional inference tree results illustrating the significant relationship between the first year vegetation growth (NDVI_1y) and solar radiation and the median percent change in total metals concentration (Bo, Cd, Cu, Fe, Mn, Ni, Pb, Se, Zn) five years after fire.....	27

KEYWORDS

Wildfire, water quality impacts, post-fire impacts on macroinvertebrates, post-fire impacts on fish, conditional inference tree, changepoint analysis, physical drivers of water quality after fire

ACKNOWLEDGEMENTS

This research has been supported by The Joint Fire Science Program, Bureau of Land Management, Award # L14AC00165

PROJECT JUSTIFICATION & EXPECTED BENEFITS

The goal of the proposed research is directly related to Task 6 from the JFSP FON (2013 RFP) and focuses on the “Effects of wildfire on water”. **Specifically, we investigate the variability of post-fire water quality response and determine the key drivers impacting the immediate contaminant flux, recovery over the longer-term and ultimate resiliency of impacted watersheds and municipal water supplies.** Our work includes collection and synthesis of historical pre- and post-fire water quality data, analysis of new geochemical data, and statistical and hydrochemical modeling in burned watersheds.

The expected benefits from this research include improved understanding of the spatial and temporal variability in water quality after wildfires, including longer-term recovery processes, as well as models that can predict short and long-term hydrochemical response to aid in regional resource and management decisions. A key deliverable from our work is an extensive database that can be utilized by the community for regional water quality analysis and model development.

PROJECT OBJECTIVES

Objective 1 - Developed a comprehensive database of available water quality observations in the Western U.S. for over 24,000 burned watersheds from 1985 to 2012. Intense data mining included acquisition and compilation of western pre- and post-fire water quality data, including USGS, USFS, EPA, and state agencies databases. All data has been checked, organized, and compiled by state into one easy to use database. This work may require on-going funding support to pay someone to continue the update-process beyond the life of this grant. The database is one of the deliverables of the project.

Objective 2 - Supplemented the existing water quality database with ongoing work in the West Fork Complex Fire where the PI has ongoing projects monitoring post-fire water quality. We have completed four years of water quality monitoring on the Rio Grande and its tributaries in the areas impacted by the 2013 West Fork Complex Fire. We have collected a tremendous amount of water quality data; including data on nutrients, suspended sediment, and metals in the burned watersheds.

This data is included in the JFSP database. In addition to water quality data we have collected biological data on macroinvertebrate and fish populations to evaluate water quality impacts on biota. Observations from this study reveal the fish and insects recover quickly, within 3 years after the fire. We continue to share our results with the community impacted by the fire, updating people on the rapid ecosystem recovery.

Objective 3 - Collected and analyzed spatial and temporal geophysical, climate and remote sensing data in burn areas where water quality data are available. We have leveraged partial funding from the USGS to support a graduate student who has compiled geophysical parameters: soils, land cover, topography, aridity, and burn severity of the same 300+ watersheds. The study by Saxe et al. (2018) examines how these geophysical parameters impact hydrologic response (low and peak flows, flashiness and baseflows). This research has been published in the journal of Hydrology and Earth System Science (HESS).

Objective 4 – Utilized the vast amount of data compiled in our fire-water quality database to determine trends in water quality response. Findings from this study show a significant increase in nutrient concentrations and flux (different forms of nitrogen and phosphorus), major-ion flux, and elevated suspended metal concentrations are the most common responses after fire. Elevated loading rates of these constituents persist for five years after fire. This analysis is complete and has been published in the International Journal of Wildland Fire (Rust et al., 2018).

Objective 5 – Statistical modeling to determine key drivers of short and long-term water quality response and resiliency. Building on the post-fire water quality trend analysis in Objective 4, we have evaluated physical drivers that influence water quality response and recovery times. This project combines what has been learned from the papers produced in Objective 3 and Objective 4. A publishable paper summarizing this analysis is under internal review with our co-authors. A manuscript is under preparation and will be submitted for publication by November 2018.

1. WATER QUALITY IMPACTS FROM THE WEST FORK COMPLEX FIRE: MONITORING ECOSYSTEM HEALTH AND RECOVERY IN THE UPPER RIO GRANDE

Modified from a manuscript in preparation for publication
Ashley J. Rust, Terri S. Hogue, Jackie Randell, and Andrew Todd

1.1 Introduction

Forest fires burned more area in the last three decades than in any previous time (Miller 2009). In the 2017 season, wildfire consumed 44% more area in the Western United States than the average ten years ago (National Interagency Coordination Center, 2017). This is partly due to climate change, which contributes to increasing wildfire frequency and size (Westerling et al. 2006; Morgan et al. 2008; Westerling et al. 2011). Wildfire seasons are longer with warmer spring temperatures and earlier snowmelt leading to inevitable fires (Westerling et al. 2006; Running,

2006). Warmer, drier conditions will continue to drive an increase in fire activity across the globe (Pechony and Shindell, 2010). Climate models predict continued warming in the Western United States, leading to a predicted 200% increase in total area burned in the Southwestern U.S. (Spracklen et al. 2009). Forest fires change vegetation, alter soils, and affect water quality in disrupted watersheds (DeBano 2000; Smith et al., 2011; Burke et al. 2013), which can devastate the aquatic ecosystem including sensitive aquatic macroinvertebrate species and trout (*Salmonidae*; Minshall 1989 and 2001; Howell 2001; Burton 2005).

Previous studies have generally focused on singular effects of wildfire on aquatic systems; where some studies analyze the impacts on water quality while another evaluates the impacts on macroinvertebrates or fish. In this research, we investigate wildfire impacts on water quality, macroinvertebrate, and fish populations in streams directly below the second largest forest fire in Colorado's history. Our goal is to holistically evaluate a wildfire's impacts on an aquatic ecosystem. Data was collected over a 3-year period on all aspects of water quality: sediment, nutrients, metals, dissolved oxygen, and temperature above and below a large wildfire. We also collected macroinvertebrate samples above and below the fire and compared results to pre-fire population data. Finally, we included fish population monitoring in a small fire- impacted tributary and the mainstem of the river below the fire.

1.2 Background and Study Site

The West Fork Complex (WFC) fire consumed 44,360 hectares (444 km²) in Colorado during the summer of 2013. It was the second largest wildfire in the state's history. The complex of three fires in the upper Rio Grande watershed, located in Southwestern Colorado, were ignited naturally by lightning strikes (Figure 1). The majority (88%) of the burn area was comprised of Engelmann spruce (*Picea engelmannii*) trees killed previously by Spruce Beetle (*Ips spp.*). Damage to the soils was of moderate to high severity in the majority of the area (60%; USDA 2013). The Rio Grande provides excellent recreational fishing opportunities from the reservoirs at the headwaters through the miles of Gold Medal Stream as designated by the Colorado Parks and Wildlife (CPW) and supports an abundance of trophy trout (Colo. Wildlife Commission, 2008). Many local fishing businesses take advantage of the extraordinary large stonefly (*Pteronarcydae*) that hatches in early summer, feeding the large trout and creating excellent fishing opportunities for tourists.

1.3 Methods

Streamflow, physical and chemical water quality, macroinvertebrate and fish populations were monitored for three years after the WFC fire, control or unburned sites were compared to impact sites surrounded by or below the fire. We compared macroinvertebrate data and metals concentration data to historic data. A total of ten sites were monitored during this study. Five study sites were chosen in the Upper Rio Grande, a sixth site was in the South Fork of the Rio Grande and four additional study sites were selected as paired control-impact tributaries in the Upper Rio Grande (Figure 1, Table 1). One site, at Thirty Mile, was upstream of the fire and served as the control site for the Rio Grande. Five impact sites were below the fire in the Upper Rio Grande and the South Fork of the Rio Grande. Additionally, of the four tributary sites selected two were control and two were impact; tributary sites were paired, where one tributary in each pair was within the

burn area (impact) and one tributary in each pair was in a sub-watershed outside of the fire (control) (Table 1).

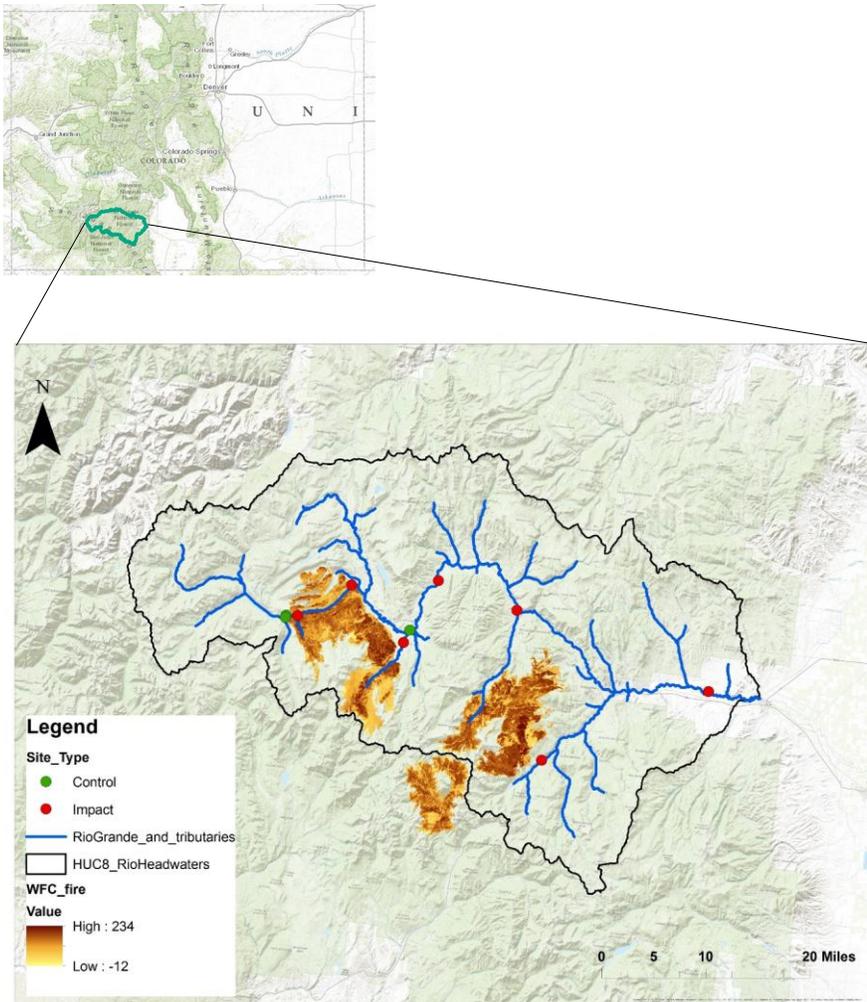


Figure 1. The Upper Rio Grande watershed in southwestern Colorado. Colorado is shown above for reference where the watershed is highlighted in green. The West Fork Complex fire shown here, burned 110,000 acres of this steep headwaters watershed.

Streamflow.-- Stage height was monitored at each of the ten sites. The Colorado Division of Water Resources (CDWR) operated stream gauges at the six sites on the Upper Rio Grande and South Fork of the Rio Grande. In the four tributary sites, Hobo Water Level Loggers were installed in stilling wells to record pressure. Stream height was recorded at the stilling well and streamflow was measured in the field following the US Geological Survey (USGS) mechanical current meter method (Buchanan and Somers 1969). Recorded pressure levels were correlated to field measurements of flow and stage height to build rating curves.

Water quality.-- High resolution temporal water quality monitoring was conducted at each of the ten sites. We deployed a Hydrolab MS5 multiparameter water quality sonde at each site to record stream temperature, pH, specific conductivity, total dissolved solids, and dissolved oxygen. In 2015, two years after the fire, a turbidity sensor with a detection limit of 0 - 3000 NTU's was added to each sonde. The multiprobes were installed in stilling wells in conjunction with the Hobo Water Level Loggers from May to October 2014-2016. Data were recorded continuously every fifteen minutes at five of the sites where the multiprobes were powered by the CDWR stream gauge. At the other five sites, where the probes were battery powered, data were recorded every three hours. The sondes were checked for debris, cleaned, calibrated, and data downloaded every two weeks. Upon each site visit, a Hach Colorimeter DR 900 was employed to test nitrate, nitrite, and phosphorus (as orthophosphate) with a detection limit of 0.02 mg/L orthophosphate. The field colorimetric methods used were: Nitrate Cadmium reduction method for low range nitrate, with a detection limit of 0.01 mg/L nitrate and a Nitrite USEPA Diazotization Method, Phosphorus USEPA PhosVer3 (Ascorbic Acid) Method with a 0.003 mg/L nitrite detection limit (USEPA 1979). Also, upon each site visit, grab samples were collected to later analyze for total suspended solids. Total suspended solids samples were analyzed in the Colorado School of Mines Hydrology lab following the US Environmental Protection Agency (USEPA) ESS Method 340.2, Total Suspended Solids, Mass Balance methodology (USEPA 1993). Water quality data collected for fire-impacted sites were compared to data from control sites and when possible, data were compared to Colorado's state water quality standards. Since Colorado does not have a suspended solids or turbidity standard, we used 50 NTU as the acute threshold for trout and compared sediment conditions to the control streams as the normal condition to evaluate whether turbidity or total suspended solids are 10% above normal conditions (Rowe et al. 2003).

Dissolved and total metals samples were collected twice per year during high and low flow events and analyzed by inductively coupled plasma mass spectrometry (ICP MS, Water-Mira 032713U method).

Statistical Analysis.-- To determine if there were any detectable changes in analyte concentrations below the fire, non-parametric statistical techniques were used, thereby not assuming normal distribution of the water quality data. The Mann-Whitney *U* test is a rank sum test, reducing the impact of outliers (Helsel and Hirsch 1992); assumptions for the Mann-Whitney *U* test were met (Tamhane and Dunlop, 2000). This method was used to identify differences in median values (or distribution) of each water quality parameter measured above and below the fire. A non-parametric multiple comparison test, the Kruskal-Wallis test, was conducted to compare the medians of physical and chemical water quality values among all sites, and an approximate p-value for the large sample is calculated.

Macroinvertebrates.--In addition to monitoring streamflow and water quality, macroinvertebrate populations were sampled at each of the ten sites once per year, in the first week of August from 2014-2016. The state of Colorado had collected macroinvertebrate data prior to the fire from many of the same sampling sites. To identify wildfire impacts on macroinvertebrate populations, we compared our data collected after the fire to historic data. We followed the Colorado Department of Public Health and Environment (CDPHE) macroinvertebrate sampling protocols (CDPHE Policy 10-1).

The index calculated from macroinvertebrate samples was the Shannon-Wiener Diversity Index (SDI), a metric of relative species abundance where values range from zero to five higher values indicate higher species diversity (MacArthur 1965).

Fish populations.-- Fish populations on the mainstem of the Rio Grande were monitored by the Colorado Parks and Wildlife. In both the mainstem of the Rio Grande and in the tributary, fish populations were sampled by electrofishing.

Table 1. Water quality, macroinvertebrate, and fish sampling locations above and below the West Fork Complex Fire.

Site Name	Control/Impact	River	Distance from Fire (km)	Watershed Area (km ²)	Area of Watershed Burned (km ²)	Percent of Watershed Burned	Percent of Fire Moderate and High Burn Severity	Years of Sampling
Thirty Mile	Control	Rio Grande	0.2	419	0	0	0	2014-2016
Box Canyon	Impact	Rio Grande	0	552	26	2	68	2014-2016
Marshall Park	Impact	Rio Grande	11.13	1,436	63	4	65	2014-2016
Wagon Wheel Gap	Impact	Rio Grande	9.28	1,986	63	3	65	2014-2016
Del Norte	Impact	Rio Grande	22.7	3,575	108	3	2	2014-2016
South Fork at Columbine	Impact	South Fork of Rio Grande	2.28	174	12	7	5	2014-2016
Squaw	Control	Squaw Creek	0.07	55	0	0	0	2015-2016
Little Squaw	Impact	Little Squaw Creek	0	47	7	15	63	2015-2016
Red Mountain Creek	Control	Red Mountain Creek	3	82	0	0	0	2015-2016
Trout Creek	Impact	Trout Creek	1.2	101	17	17	57	2015-2016

Commented [AR1]: I recognize that I need to remove the lines in the table and colors from the boxplots before submitting to the journal of fish management, per their requirements. I will work on fixing these.

1.4 Results and Discussion

Water quality. The real-time high-resolution water quality monitoring allowed us to identify water quality impacts as they occurred. Most of the observed chemical and physical water quality parameters remained within normal ranges of state water quality standards, and water quality in the Rio Grande and tributaries below the fire were not significantly different from water quality in control sites. The median and ranges of pH, temperature, specific conductivity, dissolved oxygen concentration and percent saturation, total dissolved solids, nutrients, and metals remained equivalent among all sites, control and impact.

While many chemical and physical water quality characteristics remained unchanged after the fire, the mean and median turbidity of the streams below the fire were significantly higher than control sites (Table 2). After the observed fish kill on Trout Creek, one year after the fire in August of 2014, we started monitoring turbidity and total suspended solids initially in 2014 with handheld sensors before deploying the turbidity sensors at all locations in 2015. One day after the fish kill,

the concentration of total suspended solids in Trout Creek was 1018 mg/L. The turbidity of Trout Creek after the fish kill was 505 NTU.

Elevated turbidity and total suspended solids concentrations and the frequency of extreme turbidity values were the significant detectable water quality impacts from the WFC fire (Table 2, Figures 2 a and b). Stream segments within the burn scar and sites outside of the burn scar (but less than 12 kilometers from the fire) had significantly higher turbidity than the control sites. This includes sites along the Rio Grande and the two impacted tributaries (Table 2). Most of these significant differences are the median and distribution of the turbidity levels between control and impact sites, while other water quality parameters remained unchanged. The statistical tests revealed levels of turbidity were significantly higher at all impact sites on the Rio Grande in 2015 (Figure 2a).

The control site, Thirty Mile, is compared to the impact sites in the Rio Grande (Figure 2 a and b). The impact sites all had significantly higher median turbidity levels in 2015 (Figure 2a, Table 2). Box Canyon, the first site on the Rio Grande below the control site and in the fire scar, had mean turbidity levels that were 18 times greater than the control in 2015 (Table 2). Furthermore, turbidity values exceeded 50 NTU eleven times more often and 100 NTU fifteen times more often than the control site (p-value < 0.05 Mann-Whitney *U*). The next site downriver of the fire, Marshall Park, which is over eleven kilometers from the fire perimeter, also experienced turbidity values above 50 NTU nine times more often than the control site (p-value < 0.05 Mann-Whitney *U*). However, other down-river sites were less impacted, where turbidity values were almost identical to the control. Paired comparisons among the tributary sites show a similar pattern, impact sites had significantly higher turbidity levels in 2015 and 2016. Additionally, in 2016, the fire impacted tributary had a mean turbidity of 1801 NTU and a median of 3000 NTU (p-value < 0.05, Mann-Whitney *U*). Similar observations were made in the other paired tributary sites, Squaw Creek, control, and Little Squaw Creek, impact. Little Squaw had significantly higher median turbidity levels than Squaw Creek in both 2015 and 2016 (p-value < 0.05, Mann-Whitney *U*, Table 2). The elevated turbidity levels observed in fire-impacted sites were a result of both the high flow during snowmelt runoff and the late summer monsoon rain events.

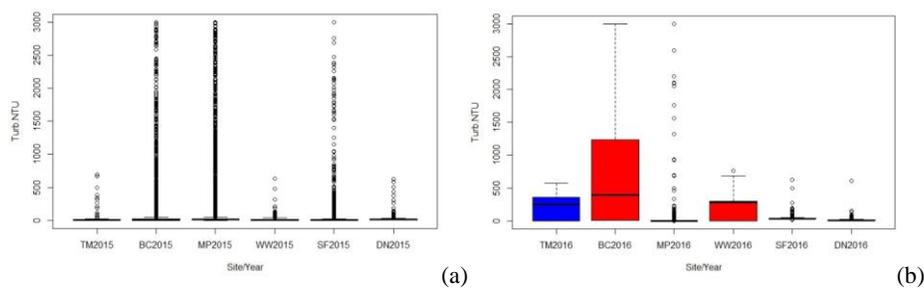
Macroinvertebrates.--We compared newly collected benthic macroinvertebrate population data with historic data from before the fire collected by CDPHE. Unfortunately, our control site had not been sampled by the state before the fire so there was no historic data at Thirty Mile for comparison. However, looking at the patterns in Figure 3, the macroinvertebrates were impacted by the WFC fire whether they lived within the fire area or near the fire. Even in the control sites, populations were observed to be impaired after the fire (Figure 3). All sites (control & impact) show a decline in the SDI. All sites fell below the impairment threshold of 3.0 the first year after the fire (Figure 10). Some sites show recovery two years after fire where the SDI value is at or above impairment thresholds, and all sites recover by the third year after fire (Figure 3). A decline in diversity and increase in pollution tolerant species were documented previously in other fire-impacted areas (Verkaik et al. 2015). All sites except the control site, Thirty Mile, show recovery where biodiversity metric levels are back to pre-fire conditions by 2016.

Fish Populations.--Trout population sampling in the Rio Grande below the WFC fire revealed that the fish population density and the number of large fish have both increased since the fire. This was not due to the stocking of fish; trout stocking practices did not change after the fire. Trout populations are larger in number and mass per acre in the Rio Grande after the fire than before the fire. However, the fish populations in the fire-impacted tributary, Trout Creek, experienced a

dramatic decline due to an observed fish kill in 2014 caused by a monsoon-driven landslide in the fire scar. Extremely high total suspended solids and turbidity levels were observed during the fish kill event. Fish sampling in 2015 revealed that there were no adults inhabiting the segment of Trout Creek below the landslide two years after the fire. Trout fry were captured - either they had been spawned in the segment, or above the landslide and young of year were washed down. Either way, the presence of young of year fish demonstrated that the water quality in the segment was suitable enough to support fish life. Looking at the comparison of the estimated population, number of fish per acre, and kilograms per kilometer in 2015 (Table 3), it is clear the site above the landslide was supporting a greater number of fish and more kilograms of fish per kilometer. The size distribution of fish above the landslide reveals a wide variety of sizes of fish, typical of a healthy population. While below the landslide, in 2015, there were only young of year fish, adults were completely absent. By 2016, the population shifts and shows dramatic recovery.

Table 2. Results from statistical comparison testing among control (Thirty Mile, Squaw, and Red Mountain) and fire-impact sites (Little Squaw, Trout, Box, Marshall Park, and Wagon Wheel Gap).

Analyte	Site & Year	Mean Control	Mean Impact	Median Control	Median Impact	SD Control	SD Impact	Mann Whitney U, p-value	Kruskal-Wallis p-value
Turbidity 2015	All Sites								2.20E-16
Turb NTU	Squaw & Little Squaw 2015	8.7	12.7	0.0	0.8	102.3	116.4	4.75E-46	
	Squaw & Little Squaw 2016	25.1	60.9	23.1	24.1	127.3	309.1	7.45E-32	
	Red Mountain & Trout 2015	87.3	21.7	3.1	4.9	468.9	136.1	1.75E-14	
	Red Mountain & Trout 2016	146.8	1801.6	0.0	3000.0	507.9	1397.1	2.05E-184	
	Thirty Mile & Box Canyon 2015	12.3	215.9	6.2	6.8	43.9	681.7	2.51E-11	
	Thirty Mile & Box Canyon 2016	257.7	697.7	0.0	8.5	582.1	1073.3	5.26E-25	
	Thirty Mile & Marshall Park 2015	12.3	144.0	6.2	10.6	43.9	534.0	4.45E-57	
	Thirty Mile & Wagon Wheel Gap 2015	12.3	17.6	6.2	7.2	43.9	43.9	5.70E-12	
NO3	Squaw & Little Squaw 2015	0.00	0.06	0.00	0.03	0.01	0.06	0.0172	
TSS 2016	Thirty Mile and Marshall Park	4.0	14.2	2.5	10.0	3.6	11.6	0.04	



Figures 2. a and b. Boxplots showing turbidity levels measured in 2015 (a) and 2016 (b) in the Rio Grande above the fire in blue, Thirty Mile (TM), and below the fire in red at Box Canyon (BC),

Marshall Park (MP), Wagon Wheel Gap (WW), the South Fork of the Rio Grande (SF) and Del Norte (DN).

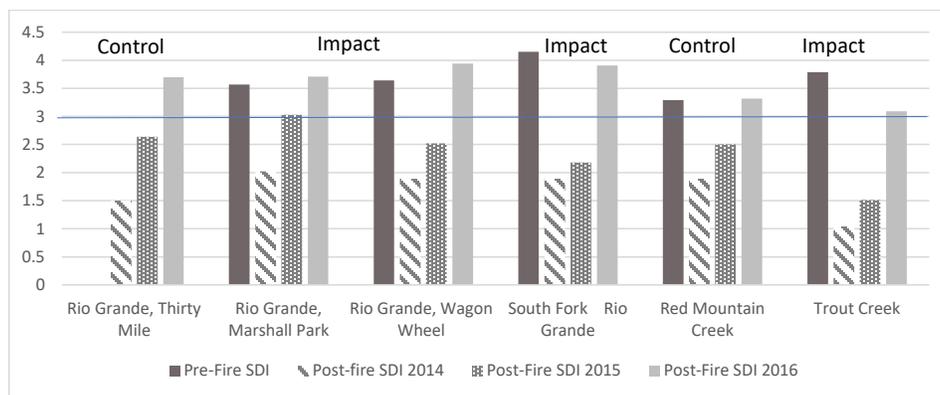


Figure 3. The Shannon Diversity Index (SDI) for control and impact sites from before the fire in 2012 and after the fire in 2014-2016. Vertical bars separate control and impact sites and sites in different streams (Rio Grande, South Fork of Rio Grande, and tributaries, Red Mountain and Trout Creek). The Shannon Diversity Index is a measure of macroinvertebrate species diversity. A SDI below 3.0 is evidence of water quality impairment in the state of Colorado.

Results show significant post-fire water quality effect in the form of elevated turbidity and total suspended solids, and this water quality perturbation was observed to have had direct impacts on fish. Macroinvertebrates were affected by the fire in a different way. The fish and insect populations recovered to pre-fire levels and populations were not significantly different in control and impact sites three years after the fire despite continued elevated turbidity.

Aquatic life thresholds for turbidity and total suspended solids are not widely known. Suspended sediment and turbidity conditions are highly variable in streams. The duration, timing and particle size of the high sediment concentrations determine the effect on resident fish. Bilotta and Brazier (2008) documented current literature which demonstrated that a range of suspended solids concentrations from 47 mg/L to 40,000 mg/L can kill salmonids in different life stages. Elevated sediment concentrations have the largest impact on trout during low flow conditions and when water is warm (Bilotta and Brazier 2008).

While many of the other water quality parameters that we monitored were not significantly different between sites upstream or downstream of the fire, turbidity levels below the WFC fire were significantly higher than control sites. The median turbidity and frequency of exceedances over the threshold were higher in stream segments that were closer to the fire and below fire areas where there was moderate and high burn severity. The four sites within 12 kilometers of the fire

perimeter and in watersheds where the majority of the fire was moderate to high severity (> 63% of fire moderate to high severity) had significantly higher turbidity levels two years after the fire (Table 1 and 2). The monitoring site that was 22 kilometers away from the fire and at the outlet of the study watershed, where only two percent of the fire was moderate to high severity, had no significant change in turbidity or total suspended solids levels after the fire. Fire severity and proximity drove the turbidity response in 2015. By 2016, elevated turbidity levels and frequency of extreme values were only observed in the fire impacted tributaries and the Rio Grande site within the fire scar.

Table 3. Fish population metrics above and below the landslide in Trout Creek one year after the landslide and two and three years after the fire.

		N (pop. est.)	Standard Error of N	Confidence Limits of N	Number per acre	Kilograms per kilometer
Above Landslide	2015	24	8	24 +/- 16	93	5
	2016	24	1	24 +/- 2	142	16
Below Landslide	2015	7	1	7 +/- 2	43	0
	2016	28	3	28 +/- 6	151	5

1.5 Conclusion

While water quality was still impaired, with high turbidity levels three years after the fire in locations directly below the fire scar, aquatic life was generally recovered in the Rio Grande. Fish populations were documented to be improving and macroinvertebrate population and diversity had recovered. Observing a decline in insect diversity and abundance in control sites was an unexpected result. It is possible that insect populations were more perturbed by air pollution than stream water quality, however, this hypothesis remains untested and would merit further research. Future studies should investigate the extent of the area around a fire’s perimeter that impacts macroinvertebrate populations.

Trout appear able to tolerate elevated turbidity in large connected streams like the Upper Rio Grande, where they can move out of poor water quality and take refuge up and downstream of turbid waters. This is evident in the state’s fish population estimates in the Rio Grande. However, where fish are trapped in small tributaries water quality impacts can be deadly, but still, the populations rebound quickly. Continued monitoring of water quality, aquatic life and vegetation recovery for the three to five- year period after fire could help identify determinants of system-wide recovery. Ultimately correlating vegetation recovery to water quality and aquatic life abundance could also inform land and water resource managers on how best to support ecosystem resiliency.

2. Post-fire water quality response in the Western United States

Ashley J. Rust, Terri S. Hogue, Samuel Saxe, and John McCray
(From Rust *et al.* 2018)

2.1 Introduction

Large wildfires are increasingly common in the western United States. Wildfires impact water resources, already in high demand in the arid West. Since the mid-1980s, warmer spring and summer temperatures, coupled with lower than average precipitation, produced longer wildfire seasons causing more frequent and larger fires (Westerling *et al.* 2006; Morgan *et al.* 2008; Westerling *et al.* 2011). Consequently, forest fires burned more area in the last three decades than in previous time periods (Miller 2009). As climate models predict continued warming in the Western United States, total area burned by fire is expected to also increase into the future (Spracklen *et al.* 2009) and may even lead to changes in vegetation types and fuel load (McKenzie and Littell 2016). Models predict that burn areas in the Western United States will increase by 50% to 100% over the next fifty years (McKenzie *et al.* 2004; Spracklen *et al.* 2009; Harvey 2016). Given that the Western U.S. is a large region with a variety of ecotones, findings about the growth and extent of fire could be further applied to a broader global scale.

Wildfires not only disturb vegetation but change soil structure altering hydrological processes and water quality in fire-impacted watersheds. As wildfires consume even more forested areas, water supplies and aquatic ecosystems are increasingly affected. In addition, forested mountain areas of the Western United States receive high quantities of precipitation and are the source of high quality drinking water for millions of customers (Bladon *et al.* 2014). Wildfires are known to impact water quality and can threaten these downstream drinking water supplies (Smith *et al.* 2011; Bladon *et al.* 2014). Furthermore, the surface waters of the arid West are limited and in demand by aquatic ecosystems, irrigated agriculture, and the region's growing human population. Ultimately, studies on individual wildfires demonstrate these impacts on water quality and quantity in a water-scarce region (Runge and Mann 2008; Emelko *et al.* 2011; Bladon *et al.* 2014; Kinoshita and Hogue 2015).

With an understanding of how fires remove vegetation, alter soil properties, and lead to increased post-fire runoff, it is still unclear which chemical and physical water quality constituents will be impacted by fire and what the magnitude and duration of that impact will be. The current study moves beyond examining the impacts of a single forest fire. Instead, this research evaluates a multitude of fires (159) over a broad spatial and temporal scale (1984-2015) to determine the most common water quality responses after fire. Utilizing public databases with historic water quality data, information was assembled to evaluate changes for a range of 89 water quality parameters in 153 rivers before and after 159 wildfires. Our goal is to better understand how fires generally alter physical and chemical water quality in receiving streams and the duration of the water quality impact. Through using a large sample size, we investigate how forest fires impact concentrations of suspended and dissolved materials in receiving streams.

2.2 Methods

Information on recent wildfires in the Western United States was acquired from the Monitoring Trends in Burn Severity (MTBS) website (www.mtbs.gov). The MTBS website provided burn perimeters, burn area, and burn severity data for each of this study's 24,042 fires from 1984 to 2015, from available satellite data. Fire perimeters were used to locate USGS stream gauges below fires. All USGS gauge stations and water quality sampling sites were mapped in ArcMap 10.1 to check their locations relative to fires, verifying all water quality samples were downstream of a fire. The USGS stream gauge locations were used to define the watershed boundaries and watershed area for each of the study's burn-impacted watersheds across the Western U.S. (Figure 4). A summary of the general physical attributes of each of the fires and watersheds that are the focus of this study is presented in Table 1.

Water quality data assembly

Pre- and post-fire water quality data were acquired by data mining federal and state water quality databases. The federal sites used were the USGS National Water Information System: Web Interface (NWIS) and EPA STORET (EPA Storage and retrieval and water quality exchange). In addition to searching national websites for available water quality data, western U.S. state public health and environmental department websites were also searched for chemical and physical water quality data; when available, data from before and after a fire were obtained. Data from the USGS NWIS were collected in the field, as grab samples, and by continuous data loggers. All data collected by the USGS follows their accepted methodology and has been finalized by the USGS. The water quality data available on EPA's STORET site and from individual state agencies has been collected in the field following accepted methodology and protocols. Water quality sampling methodologies from different agencies varied in some cases. Sampling frequency also varied for each site, some sites had semi-annual or quarterly data while other sites collected samples more frequently. At a minimum, each site collected two samples per year. Chemical and physical water quality data from different sources was then formatted in R and assembled into a database (using Microsoft Access). All dates for water quality sampling events were synchronized to water years (WY) (October 1- September 30). Water quality data for each sampling station was plotted over time to check data for obvious typographic errors, to confirm that sampling occurred throughout the five years before and after fire, and to verify results were not reported below instrument detection limits before inclusion in the database. The resultant database included fire, chemical, and physical water quality data from multiple sources with two million water quality data-points for western wildfires from 1984-2015. A total of 89 separate chemical and physical water quality parameters were included in the database and evaluated in this analysis.

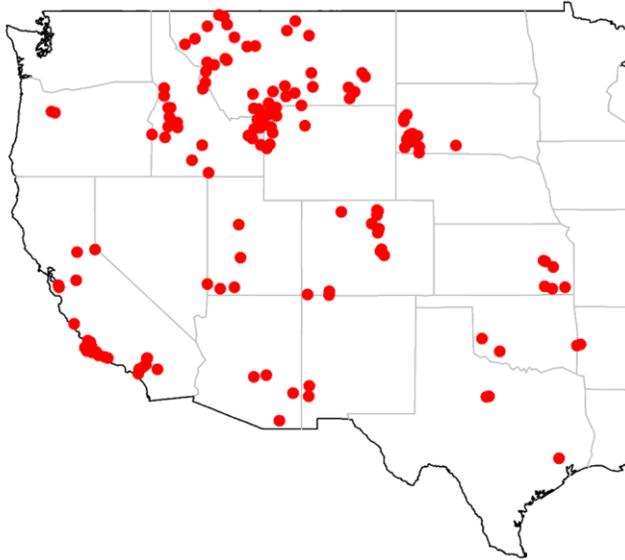


Figure 4. Map of 153 fire-impacted watersheds in the western United States with sufficient pre- and post-fire water quality data used in this analysis.

Mean daily flow from the USGS gauge stations was used along with concentration data to calculate the loading rate or flux for each of the water quality parameters. Less than 10% of the USGS gauges had missing flow data for the pre- and post-fire periods of interest. To calculate flux, mean daily flow was multiplied by the concentration of each analyte measured on the same day to give an estimate of the instantaneous rate at which the load was passing the water quality sampling station. Flux was calculated to address seasonality, climate differences, and the variability of flow that alters analyte concentrations among sites across broad regions and time periods. Flux is equally as important as concentration data when evaluating the potential impacts of water quality on an aquatic system (Helsel and Hirsch, 1992). Both changes in analyte concentration and flux are analyzed in this study.

The assembled fire-water quality database was screened to meet minimum pre- and post-fire sampling frequency for analysis. All watersheds included in this study had a minimum of ten water quality data points over the five- year period preceding fire to define baseline water quality conditions. Post-fire water quality was defined as the first five years after a fire. To evaluate water quality impact from fire, a minimum of ten records five years after fire were used to define post-fire water quality conditions. Synopsis data for all analytes evaluated in this study are included in Table 4; the number of fire impacted watersheds that had adequate data (according to screening criteria) for each analyte is also listed.

If there were multiple fires in a watershed in a single year, the burned areas were summed together and the total area was used to calculate the percent of the watershed area burned. If a fire consumed less than 5% of the watershed area, the fire would likely be too small to show meaningful effect on the water quality, therefore, these fires were eliminated from the analysis. When there was more than one fire in a watershed over a ten-year period, a clear baseline pre-fire condition could not be established; therefore, those fire-events were also eliminated from this analysis. Consequently, a minimum of ten years between fire events was required for the wildfire event to be included. Between the minimum criteria for water quality data points and the required minimum ten years between fires, just 159 out of the 24,042 fires were deemed acceptable. In summary, 159 fires which impacted 153 western U.S. watersheds are utilized for analysis in this study.

Subset analysis

In water quality monitoring, a higher frequency of sampling is generally required to detect trends in physical and chemical measures (Kirchner et al, 2004). In the current study, fire-impacted watersheds with higher frequency of sampling, such as monthly sampling, were selected from the fire-water quality database. Seven fire-impacted watersheds with monthly water quality sampling data for five years preceding and following a fire were sub-selected for analysis. Data from the subset group of seven watersheds was evaluated to look at the impact of hydrology and climate on water quality response. However, to keep results concise and avoid repetition, subset analysis results are shown for four out of the seven watersheds. Daily gridded precipitation data for each selected watershed was retrieved from the PRISM Climate Group website (www.prism.oregonstate.edu). Precipitation data was paired with daily flow data from the USGS to assess how rain and flow events influence analyte concentrations. Analyte concentration data from each of the subset watersheds were plotted over time to detect changes in analyte concentrations, providing a means to evaluate trends over time and shifts in mean analyte concentration after fire.

Statistical analysis of entire dataset

Using water quality data from all 159 fires, mean, median, and standard deviations were calculated for each analyte concentration and flux at each water sampling station over the five years pre-fire and compared to the same statistics five years post-fire. The average of the mean and standard deviations from all water sampling stations for each analyte was calculated to summarize general response to fire (Table 4). The percent change in concentration and flux was then calculated for each analyte for each of the 159 fires.

To determine if there were any detectable changes in analyte concentration and flux after fire, non-parametric statistical techniques were used, thereby not assuming normal distribution of the water quality data. Assumptions for the Mann-Whitney U test were met (Tamhane and Dunlop, 2000) and the statistical test was performed for each analyte, comparing the difference in median values (or distribution) of concentration and loading rate, or flux, before/after the fire. The Mann-Whitney U test is a rank sum test, reducing the impact of outliers (Helsel and Hirsch, 1992).

Statistical analysis for selected subset fires

To evaluate trends in water quality after fire, change-point analysis was conducted on the subset of seven burned watersheds with regular and frequent monitoring data. Change-point analysis detects a shift in mean concentration over time while controlling the change-wise error rate and provides a confidence interval for the time of change (Taylor, 2000). This method was applied to identify abrupt changes in the mean concentration of various analytes. Change-point analysis is also considered robust to outliers and is better at identifying abrupt changes in data than trend analysis (Taylor, 2000). Though, linear trend tests were also conducted in this study, by computing Kendall's Tau and Spearman's Rho (Helsel and Hirsch, 1992), no general linear trend in analyte concentration was detected over time, so no further results or discussion are shown on linear trends.

Within the subset of seven fires with high frequency sampling, time series data was sometimes irregular (monthly samples were not always taken exactly 30 days apart); however, a change-point detection technique was applied for use with irregular interval data (Gurarie *et al.*, 2009) known as behavioral change-point analysis (BCPA). This technique sweeps a "window" over the dataset and identifies the most likely change-points (Gurarie *et al.* 2009). BCPA analyzes indiscriminate time series data that by its nature is assumed to be autocorrelated and Gaussian with a mean, a standard deviation and an autocorrelation coefficient. When autocorrelation coefficient values are low ($\rho < 0.05$) the analyte concentration data points in the time series are considered not autocorrelated and are significantly different from one another. A sub-sampling window size of 40 sequential analyte concentration data points was used; this exceeded the minimum sample size required for the Bayesian Information Criterion (BIC) used in model selection. This technique detects shifts in the concentration values at a small temporal scale within BCPA (Gurarie *et al.* 2009). The BIC model was fitted through the analyte concentration data, as shifts in mean concentration were detected a change-point was identified. Change-point dates were compared to the fire date for each watershed in the subset analysis. Assumptions of the model were verified by inspecting the Q-Q plot and the autocorrelation function. The technique was implemented in R with code provided by Gurarie *et al.* (2009).

2.3 Results and Discussion

Results show that water quality changes of one form or another are common after forest fire across the 159 fires that were analyzed. Concentrations of dissolved nutrients, such as ammonia, nitrate, and total nitrogen increased in 45%, 24.5%, and 37.5% of the watersheds respectively. Concentrations of some major ions, calcium and chloride significantly decreased after 26.1% and 21.4% of the fires, while concentrations of other major ions such as sodium and potassium significantly increased after 28.8% and 30.5% of the fires. Dissolved metal concentrations significantly decreased in 11-60% of the fire-impacted watersheds. While the concentrations of some dissolved constituents decreased, their flux or loading rate over the five years following fire still significantly increased due to increased flows. In contrast to the dissolved constituents, post-fire concentrations of suspended nutrients such as total nitrogen and total phosphorus increased after 34% of fires and total metals increased after 22 to 60% of the fires; loading rates also increased. Table 4 presents a comparison of average concentrations and fluxes for each analyte before and after fire. For each analyte, the number of watersheds that met data criteria is listed in

the second column and the percentage of fires where there was a statistically significant response (where p -value < 0.05 from the Mann-Whitney U test) is listed in the last column. To detect the most common, significant changes in water quality after fire, analysis for this study focused on analytes where there was sufficient data for 20 or more watersheds. There were fewer watersheds with sufficient total and dissolved metals data, nevertheless they will be reviewed to expose some interesting results.

Nitrogen and phosphorus response

Post-fire nutrient concentrations showed the most consistent response. Concentrations of all particulate forms of nitrogen (organic nitrogen, organic nitrogen plus ammonia, nitrate plus nitrite, and total nitrogen) significantly increased in concentration and flux in the five years following fire in 24 – 34 % of the burned watersheds. Meanwhile, concentrations of some dissolved forms of nitrogen (dissolved organic nitrogen and dissolved total nitrogen) tended to decrease significantly in 37.5% of the burned watersheds (Table 4). Additionally, concentrations of phosphate and phosphorus also increased in the five years after fire. When taken with the increases in stream discharge after average rain and snow events, the loading rate of all forms of nitrogen and phosphorus significantly increased one third of the time. However, it is clear from the subset analysis that averaging analyte concentration data over the five-year period could be muting even more dramatic spikes in dissolved and total nitrogen and phosphorus concentrations so that the frequency of nutrient response immediately after fire could be even higher. Averaging data over the five year post-fire time period missed short-term significant responses, and instead only the most extreme and long-lasting nutrient responses were found to be significant.

Other studies on individual fires agree with our findings and have also observed an increase in nutrient concentrations and loadings after fire (Belilas and Rodá 1993; Bladon *et al.* 2008; Earl and Blinn 2003; Mast and Clow 2008; Ranalli 2004; Rhoades *et al.* 2011; Riggan *et al.* 1994). However, our study utilizes data from hundreds of fires to investigate systematic impacts on water quality across the western U.S.

Major ions

Changes in major ion concentrations after fire demonstrate a similar pattern: in one out of three fires, most dissolved ions decrease in concentration but increase in flux. Specifically, concentrations of inorganic major ions such as sulfate, calcium carbonate, dissolved calcium, and hardness all tend to decrease in concentration while still increasing in flux in the five years following fire 28-31% of the time (Table 4). However, dissolved magnesium, sodium and potassium significantly increased in both concentration and flux in 28 - 30% of more than 31 burned watersheds. The increase in loading rate of the four major ions (Ca^{2+} , Mg^{2+} , Cl^- , and SO_4^{2-}) and hardness in the 3-5-year period after wildfire is similar to observations made by Earl and Blinn (2003) and Belilas and Rodá (1993) where an increase in calcium and potassium were measured in overland flow on individual fires. While the loading rate of the major ions increased, the concentrations of these ions tended to decrease on a five-year average. Again, this is likely a result of coarse temporal sampling, where samples may have been taken during the rising limb, the falling limb, or baseflow conditions in each fire impacted stream.

Table 4. Summary of average analyte concentration and flux data for all fires. The first column lists number of watersheds with sampling events that meet minimum data criteria. Rows where twenty five percent or more watersheds changed significantly after fire are highlighted in light gray, fifty percent or more are highlighted in dark gray.

Analyte	Number of Fires with WQ Data	Mean Conc. Pre-fire	Mean SD Pre-fire	Mean Flux Pre-fire	Mean Flux SD Pre-fire	Mean Conc. Post-fire	Mean Conc. SD Post-fire	Mean Flux Post-fire	Mean Flux SD Post-fire	Perc. Change Mean Conc.	Perc. Change Mean Flux	% Fires Sig. Change MWU
SpC.us/cm	145	648.2	188.8	NA	NA	705.1	437.8	NA	NA	23.3	NA	42.9
Temp.Water	152	12.2	6.1	NA	NA	12.0	5.9	NA	NA	-0.4	NA	13.2
pH	61	8.0	0.3	NA	NA	8.0	0.3	NA	NA	0.3	NA	26.6
ANC.mg/L	12	146.8	26.5	270098.2	164755.6	130.6	24.2	250550.4	225226.7	-5.9	338.4	20.0
Alkalinity.mg/L	2	94.5	23.0	584.4	1740.6	69.6	10.2	5365.7	10542.6	-26.4	818.1	100.0
DO.mg/L	46	9.6	1.5	21510.9	21637.1	9.8	1.6	23239.1	23204.8	3.0	127.4	17.2
DO.%Sat	44	101.1	11.8	NA	NA	101.8	11.9	NA	NA	1.3	NA	21.3
Hardness.mg/L	43	265.4	68.5	165194.4	107420.3	255.1	71.5	157303.4	141016.1	-3.4	171.0	32.9
HCO3.mg/L	5	112.6	16.7	726130.3	474442.1	104.4	17.6	337041.3	236497.2	-11.4	69.4	28.6
CO3.mg/L	2	1.4	2.5	13297.0	3064.0	1.2	1.1	1375.9	2464.5	-36.9	-32.5	0.0
CO2.unfilt.mg/L	35	3.2	2.4	6046.7	16686.2	2.6	1.5	3022.5	4066.3	-7.5	460.0	22.4
Turb.NTU	12	12.8	22.4	NA	NA	702.9	1354.4	NA	NA	2350.4	NA	15.8
TSS.mg/L	3	2.8	4.0	4216.4	21890.7	12.9	20.4	78831.0	366109.0	244.6	89.3	25.0
TDS	3	257.9	56.9	NA	NA	226.8	51.5	NA	NA	-7.0	NA	0.0
Ca.filt.mg/L	47	60.3	15.0	44237.5	28944.2	56.3	15.1	42015.5	37436.3	-3.5	193.6	26.1
Cl.filt.mg/L	41	67.9	29.0	36630.5	25887.7	67.8	34.0	39821.4	43997.8	-1.3	176.8	21.4
Mg.mg/L	42	57.1	21.1	22020.3	20031.5	33.7	12.0	19010.4	14095.2	25.8	358.6	28.2
Na.filt.mg/L	35	82.1	34.5	35525.8	24357.0	83.0	34.6	43403.1	38476.0	5.9	225.8	28.8
Na.fraction.cations%	31	30.8	3.0	NA	NA	30.1	3.0	NA	NA	-2.2	NA	24.1
SO4	34	1.8	0.5	NA	NA	1.8	0.6	NA	NA	-5.0	NA	24.2
K.filt.mg/L	31	4.1	1.0	3723.3	2618.1	4.1	1.0	4616.5	3567.7	2.4	924.7	30.5
SO4.filt.mg/L	40	176.6	63.7	53560.1	34249.4	173.9	66.3	53302.0	44445.1	0.4	187.8	30.4
OC.filt.mg/L	4	5.2	2.2	11275.6	17813.2	5.3	3.7	13697.7	18041.8	23.3	32.3	16.7
OC.unfilt.mg/L	5	6.6	2.7	13883.2	20749.2	8.4	3.2	13021.9	19121.0	42.9	164.8	28.6
Org.N.filt.mg/L	7	0.4	0.1	629.2	980.0	0.3	0.1	404.6	696.5	-6.7	75.6	37.5
Org.N.unfilt.mg/L	39	0.6	0.5	1422.5	2154.2	1.6	2.8	4582.6	7039.8	150.2	1056.2	34.0
NH3.filt.mg/L	46	0.1	0.1	110.6	147.5	0.1	0.1	84.1	108.6	2.9	216.9	45.2
NH3.unfilt.mg/L	13	0.1	0.1	130.5	160.8	0.1	0.1	154.1	262.7	66.9	438.8	22.2
NH3plusOrgN.filt.mg/L	7	0.4	0.2	676.4	1050.0	0.3	0.1	459.6	813.0	-4.3	97.8	25.0
NH3plusOrgN.unfilt.mg/L	28	0.6	0.4	1835.8	2654.7	0.8	1.0	2220.4	3669.3	43.2	182.7	38.2
NO2.filt.mg/L	25	0.0	0.0	22.5	22.9	0.0	0.0	25.6	29.0	1.0	176.4	23.4
NO3.filt.mg/L	26	0.5	0.3	507.6	345.2	0.5	0.4	578.5	558.8	15.5	406.9	24.5
NO3plusNO2.filt.mg/L	39	0.6	0.3	524.6	426.7	0.7	0.4	735.3	701.5	63.6	3554.4	33.3
NO3plusNO2.unfilt.mg/L	4	0.7	0.3	850.2	699.2	0.6	0.5	227.8	381.4	502.3	451.8	28.6
TN.filt.mg/L	7	1.7	0.6	1453.9	1682.3	1.2	0.5	730.3	1145.9	-5.8	75.4	37.5
TN.unfilt.mg/L	29	1.4	1.3	3071.5	5021.9	1.4	1.1	2921.9	3880.1	35.8	150.0	34.2
OP.filt.mg/L	40	0.3	0.2	247.7	241.5	0.3	0.2	294.3	300.5	32.2	3872.4	36.4
PO4.unfilt.mg/L	39	0.6	0.3	798.5	375.4	NA	NA	NA	NA	NA	NA	0.0
P.filt.mg/L	18	0.1	0.1	155.3	179.0	0.1	0.1	165.1	200.3	5.9	197.1	18.2
P.unfilt.mg/L	46	0.3	0.4	396.5	716.0	0.5	1.1	600.5	1705.9	265.8	257.6	34.6
Ag.filt.ug/L	14	0.8	0.1	3.2	2.9	0.7	0.0	3.3	3.3	-26.6	33.4	15.8
Ag.unfilt.ug/L	4	0.6	0.2	0.5	0.6	0.4	0.1	0.3	0.3	-43.8	-55.6	50.0
Al.filt.ug/L	14	36.0	69.5	109.2	197.4	24.0	25.7	69.0	103.0	69.4	266.1	27.3
As.filt.ug/L	20	4.2	1.6	11	7	4.9	2.5	11	7	0.1	83.9	28.1
As.unfilt.ug/L	19	29.0	12.3	45.8	21.0	30.4	18.3	47.2	26.7	50.9	149.1	33.3
Ba.filt.ug/L	14	44.4	12.9	141.9	108.4	43.7	12.1	98.0	80.4	1.7	99.5	30.0
Ba.unfilt.ug/L	7	102.7	90.0	112.4	118.2	158.0	235.3	157.6	382.6	100.5	281.3	33.3
Be.filt.ug/L	12	0.7	0.5	2.2	2.6	0.2	0.1	1.4	1.5	-48.6	-2.4	62.5
Bo.filt.ug/L	13	223.0	59.4	29.9	30.5	199.0	55.1	33.5	38.8	-4.9	428.2	25.0
Bo.unfilt.ug/L	8	102.1	39.9	77.7	55.7	102.6	62.2	108.6	130.1	17.5	208.4	18.2
Cd.filt.ug/L	15	0.6	0.2	3.0	3.4	0.4	0.0	2.2	2.5	-15.0	53.2	44.4
Cd.unfilt.ug/L	11	0.5	0.2	1.4	1.6	0.2	0.3	0.3	0.6	-28.2	72.8	60.0
Cr.filt.ug/L	14	2.1	1.2	4.2	5.3	1.0	0.7	6.1	11.0	-3.5	90.5	20.8
Cr.unfilt.ug/L	12	4.5	4.5	6.0	7.9	4.1	7.3	4.2	8.3	40.4	9.9	46.7
Co.filt.ug/L	8	3.0	0.5	15.3	12.6	2.3	0.2	14.0	13.9	-22.7	-8.5	20.0
Cu.filt.ug/L	26	2.9	2.2	10.3	18.6	2.2	1.4	7.2	10.7	-1.9	68.4	30.6
Cu.unfilt.ug/L	17	10.8	12.9	16.4	23.8	15.6	31.1	21.0	52.8	79.0	228.3	40.9
F.filt.mg/L	38	0.5	0.1	556.5	365.5	0.5	0.1	602.3	583.4	-0.2	257.1	23.8
Fe.filt.ug/L	26	42.0	74.1	63.5	120.1	41.5	27.8	46.6	60.2	77.0	9076.7	19.1
Fe.unfilt.ug/L	11	2222.6	2604.6	2360.4	3739.0	3165.1	5773.2	2684.7	5099.7	179.2	244.0	23.8
Li.filt.ug/L	8	32.5	8.4	147.5	66.0	34.6	8.4	107.8	56.0	-8.4	150.4	15.4
Mo.filt.ug/L	9	8.4	1.2	46.9	39.5	7.3	0.7	42.6	42.3	-10.5	-6.9	18.2
Mn.filt.ug/L	28	40.2	28.0	20.6	22.5	28.8	31.4	12.9	14.8	37.1	182.7	34.6
Mn.unfilt.ug/L	19	209.8	290.3	191.2	301.3	1463.4	3653.9	966.0	2331.2	497.1	5089.4	20.0
Ni.filt.ug/L	18	6.4	6.3	9.8	17.7	3.3	2.6	4.8	7.3	-14.7	63.6	11.1
Ni.unfilt.ug/L	15	7.2	7.9	6.1	8.7	12.1	19.2	11.4	23.8	117.1	203.5	22.2
Pb.filt.ug/L	17	2.5	2.3	8.2	12.4	0.7	0.5	3.0	4.0	-26.7	26.0	50.0
Pb.unfilt.ug/L	15	17.8	25.1	12.6	25.0	50.3	127.7	39.7	120.5	227.6	633.4	32.0
Se.filt.ug/L	23	1.3	0.5	2.0	2.0	1.2	0.5	2.0	2.1	-2.8	130.0	28.6
Se.unfilt.ug/L	19	1.4	0.7	0.8	1.0	1.3	0.7	0.7	1.3	8.0	86.6	38.1
Si.filt.mg/L	28	16.0	6.7	22467.3	19473.3	15.1	2.8	22133.3	21209.2	-1.6	354.5	16.4
Sr.filt.ug/L	7	442.6	98.0	1172.7	641.2	561.4	105.3	922.2	606.3	-2.5	234.4	27.3
Zn.filt.ug/L	24	10.3	9.0	35.9	53.2	6.5	4.8	20.0	29.1	-2.1	Inf	17.1
Zn.unfilt.ug/L	16	40.5	55.5	44.2	62.1	88.6	229.0	71.7	199.0	85.1	262.8	24.0

Metals

The final grouping of analytes to examine are the dissolved and particulate metals. Fewer watersheds had adequate data for total and dissolved metals. In many cases fewer than 20 fire-impacted watersheds had enough data for metals before and after a fire. When there was a statistically significant change, dissolved metals decreased in concentration after fire while particulate forms increased and loading rates of both types increased (Table 4). The specific results include: dissolved copper concentrations decreased in the five years following fire by 1.9% on average 30.6% of the time while particulate forms of copper increased in concentration by 79% after 40.9% of fires. Selenium followed the same pattern, concentration of dissolved selenium decreased in greater than 28.6% of the burned watersheds while particulate selenium concentrations increased after 38.1% of the fires. Dissolved zinc also slightly decreased in concentration by 2% after 17% of fires while total zinc concentrations increased by 85% in 24% of the fire-impacted watersheds. Arsenic, manganese, and iron were exceptions to this pattern, both total and dissolved arsenic significantly increased in concentration after 28 – 33.3% of fires. Dissolved manganese increased by 37% concentration in 34.6% of the fires while particulate manganese dramatically increased by 497% after 20% of the fires. Similarly, dissolved and total concentrations of iron increased after fire.

Although fewer fire-impacted watersheds provided sufficient data, our study found evidence of elevated metal concentrations associated with sediments and some elevated dissolved metal concentrations five years after fire. Dissolved metals can inhibit osmoregulation of fish, reducing their ability to uptake important macronutrients such as Ca^{2+} and Na^+ (Hogstrand *et al.* 1994). The change-point from the High Park fire in Colorado illustrates a dramatic increase in total iron concentrations in the Cache La Poudre river immediately following and for four years after the fire.

Subset analysis

To evaluate post-fire water quality response for trends, a more in-depth analysis was needed. A subset of fires was selected where water quality sampling before and after fire was more frequent, such as monthly water quality monitoring. This provided an opportunity to compare changes in analyte concentrations and loading rate, with the watershed's hydrology. Evaluating the subset watersheds revealed a more immediate short-term water quality response after fire that was masked when data was averaged over the five years.

The first fire highlighted in this study is the 1992 Foothills fire which impacted the Boise River. The Boise River is a snow driven hydrologic system where there was monthly water quality monitoring for a long period before and after the fire. Immediately following the Foothills fire, dissolved nitrate and nitrite, total nitrogen and total phosphate increased dramatically, raising the mean concentration of those analytes for three years (Figure 5). Runoff from snowmelt events after the fire resulted in a large flow response and corresponding elevated nutrient concentrations. Change-point analysis identified a significant decrease in the mean dissolved nitrate and nitrite, mean total nitrogen, and mean total phosphate concentrations at the end of the third year. Overall, when this watershed was evaluated with the larger data set, the nitrate and nitrite concentrations declined by 39% percent in the five years following fire, the immediate increase in concentrations the first three years are masked by the overall five-year trend.

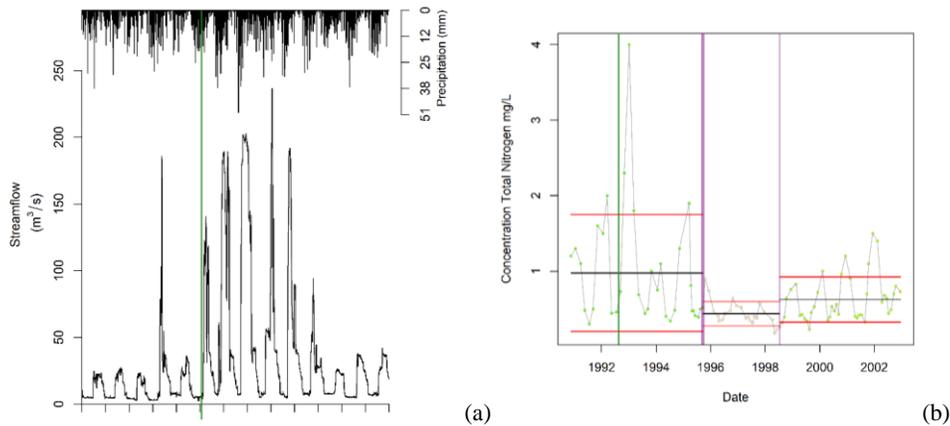


Figure 5. Hydrograph and and hyetograph (a), and flat model change-point graphs for total nitrogen(b) with data from the Boise River downstream of the Foothills Fire. Fire date is indicated with the vertical green line, purple lines show change-points, red lines show confidence intervals for the BIC model for measured concentration data.

The fire-altered landscape led to higher short-term concentrations of dissolved nitrate and nitrite, total nitrogen, total phosphate, and dissolved potassium (Figure 5). In the water year that followed the large fire, peak and annual total flows were 30 and 50 percent below average (total annual flow WY 1993 $5694 m^3$, $13,816 m^3$ average annual flow). The elevated concentrations of nutrients and ions were not due to large precipitation and flow events but instead due to the fire-altered landscape's reduced infiltration, altered vegetation and large volume of ash. As a result, below average annual precipitation (470 mm in WY 1993 compared to 830 mm average) delivered concentrations of ions and nutrients 2-5 times larger than pre-fire periods, which was detected in the change-point analysis.

In the 2003 Old Fire in southern California, mean chloride and sulfate concentrations significantly decreased immediately before and following the fire, resulting in a statistically significant change of 9%, until the change-point technique identifies a shift in the mean concentrations three years after the fire, where concentrations increased. The Santa Ana River during WY 2004 had the highest peak and annual total precipitation (104 mm and 1012 mm compared to the average peak of 48 mm and average total of 430 mm). The wet year flushed chloride and sulfate from the burned watershed and concentrations increased during precipitation events. In this semi-arid, precipitation driven watershed in southern California, flows and salt concentrations increased quickly after precipitation events.

The South Platte River in Colorado was downstream of the largest fire in Colorado's history, the 2002 Hayman fire. Here, the change-point analysis identifies an increase in total phosphorus concentrations over a three-year period caused by an immediate spike in phosphorus concentration

after the fire, which raised the overall mean concentration for the three-year period. The dramatic increase in total phosphorus following the fire occurred on a lower than average annual flow year, where total annual flows were 30% of average the year of fire (WY 2002) and 50% of average the following water year. The spike in total phosphorus corresponded with a large precipitation event the year after fire. Despite lower than average flows, due to the large precipitation event, concentrations of phosphorus were three times larger than average. Again, the total phosphorus spike was due to flushing of ash, sediment, and organic material after the fire.

The High Park fire of 2012, also in Colorado, impacted the Cache La Poudre River. Total iron concentrations increased dramatically six months following the fire, from below 500 $\mu\text{g/L}$ to 1,500 $\mu\text{g/L}$. A change-point is detected within six months of the fire date, as the peak total suspended iron concentrations increased to 3,000 and 4,000 $\mu\text{g/L}$ within a year after the fire (Figure 6). The first year after fire, WY 2012, had peak and annual flows that were 50 percent below average; despite low peak and annual flow years, peak concentration of particulate iron was five times larger than in previous years. The elevated iron concentration was not a result of increased flow volume in the Cache La Poudre the first year after fire, however, iron concentrations remained elevated in the five years post-fire and coincided with high peak flows. The higher suspended iron concentrations immediately after the fire and in the years that follow could be flushing events, where iron bound to sediment from steep slopes was washed down during snowmelt runoff events.

Commented [AR2]: Move to discussion

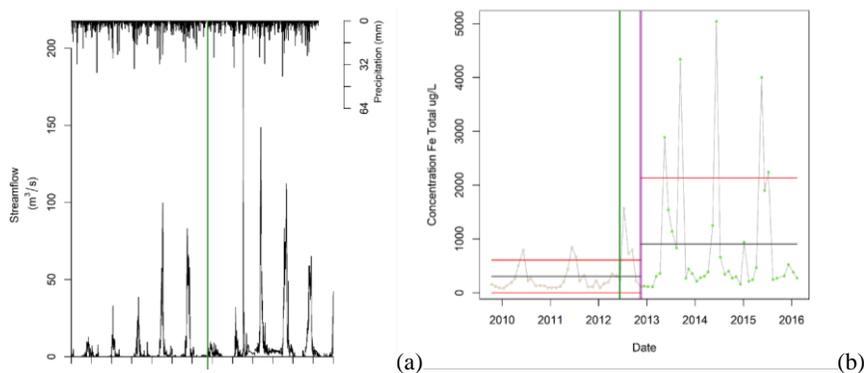


Figure 6. Hydrograph and hyetograph (a), and flat change-point model graph (b) for total iron concentrations with data from the Cache La Poudre River downstream of the High Park Fire. Fire date is indicated with the vertical green line, purple lines show change-points, red lines show confidence intervals for the BIC model for measured concentration data.

The other three fires selected for subset analysis showed similar results using change-point analysis. The Angora Fire in California showed a statistically significant elevated total and dissolved nitrogen and phosphorus response within two years following fire. When the data was averaged over five years the nutrient response was not statistically significant. The Taylor Creek fire in Montana demonstrated a short-term decline in major ions such as magnesium, that was not

detectable when the data was averaged over the five-year post-fire time period. The two fires that impacted Spring Creek in Texas show an immediate dissolved and total nitrogen response that was determined to be statistically significant with the change-point analysis.

Our research suggests that suspended nutrients and metal concentrations are the most common water quality response after fire. Metals and nutrients bound to sediments are more easily removed and transported with runoff from the denuded landscapes.

2.4 Conclusion

The overarching goal of this study was to determine the most common water quality response after wildfire across broad regions of the western U.S. Studies on individual fires do not reveal general changes in post-fire water quality; evaluating a larger dataset was necessary to identify the general response from fire. Results show that nutrient concentrations and mass loading rates of nitrate, nitrite, orthophosphate, phosphate, total and dissolved phosphorus increased after 22-38% of fires. Concentrations and flux of some ions (calcium, magnesium, chloride and sulfate) each increased significantly after 20-30% of fires. Total metal concentrations and flux also significantly increased after 25-50% of fires. Analytes bound to sediments, such as phosphorus and metals, tended to increase after fire, while their dissolved counterparts did not. Comparing time series data for analyte concentrations to daily precipitation and flow data demonstrates that precipitation events after fire resulted in increased particulate concentrations and analyte loading rates.

Not all fire-impacted watersheds experienced a significant and detectable change in water quality. Although, a significant post-fire water quality response may still occur on a shorter time scale. Shorter-term water quality responses were undetectable when data was averaged over five years. Evaluation of the subset of watersheds with higher temporal scale data revealed that water quality changes are occurring in less than five years and can be masked when the data is averaged over five years. Our analysis also evaluated whether burn severity, burn area, and aridity index were correlated to the magnitude of the water quality response. These three physical factors were not the sole drivers of water quality response. There are more geographical, physical, climatological, and biological differences among watersheds that may be determining the magnitude and direction of the post-fire water quality response.

3. Evaluating the Factors Responsible for Post-Fire Water Quality Response in Forests of the Western USA

Ashley J. Rust, Samuel Saxe, John McCray, and Terri S. Hogue

3.1 Introduction

Wildfires commonly increase total suspended solids (Silins et al., 2009; Noske et al., 2010; Smith et al., 2011; Dahm et al., 2015), nutrients (Burke et al. 2005; Mast and Clow, 2008; Rhoades et al., 2011; Writer et al., 2012), and metal export from burned catchments (Burke et al., 2013; Burton et al., 2016), though the degree and duration of responses vary widely. For example, ash inputs often increase stream pH, nutrients and cations immediately after a wildfire, but then return to pre-fire conditions within months (Earl and Blinn 2003; Rhoades et al. 2011). In contrast, wildfire in Canadian boreal forests elevated dissolved and particulate phosphorus (Burke et al. 2005) and a severe wildfire in Colorado montane forests elevated nitrate and turbidity (Rhoades et al. 2011) for more than four years. In the Canadian Rockies, post-fire stream phosphorus concentrations remained elevated in some, but not other adjacent tributaries for six and seven years after a fire (Emelko et al. 2015). Our previous work documented altered post-fire water quality in 29% of western US watersheds the first five post-fire years (Rust et al. 2018). Though post-fire water quality responses are commonly expected, understanding of the factors that regulate the magnitude and duration of these changes remain poorly understood.

There are multiple factors that affect how wildfires alter the composition of streamwater and watershed exports. Wildfires combust vegetation or surface organic soil layers, exposing hillslopes and watersheds to post-fire erosion and nutrient losses. Post-fire responses are closely linked to wildfire extent and severity (Riggan et al., 1994; Townsend and Douglas, 2004; Arkle *et al.*, 2010; Rhoades et al., 2011), but they are also influenced by catchment and soil conditions that regulate erosion and climatic and ecological conditions that determine rates of vegetation recovery. For example, post-fire drought and slow recolonization of severe wildfire patches delay post-fire forest establishment (Abatzoglou and Williams 2016; Chambers et al. 2016; Wang and Zhang 2017; Stevens-Rumann et al. 2018) and prolong effects on watersheds and streams. Reduced plant nutrient and water demand influence stream discharge and nutrient export from burned watersheds (Murphy et al., 2012; Kinoshita and Hogue, 2011 and 2015; Saxe et al. 2018) and the rate of revegetation may influence post-fire watershed recovery. Proximity to urban air pollution sources has also been shown to influence post-fire nitrate and metal export (Riggan et al., 1994; Burke et al, 2013). Local and regional factors interact in spatially and temporally complex ways with wildfire severity to determine how fires alter water quality.

The goal of the current study is to identify climate, watershed and vegetation factors that influence post-fire water quality response and recovery on an annual to decadal scale. The ability to anticipate post-fire water quality issues and identify their causes has emerged as a research priority (Moody et al. 2013; Nunes et al. 2017) that aims to better inform water treatment, land management and post-fire restoration strategies and confront challenges of increased frequency, size and severity of wildfires in the western US.

3.2 Methods

We continued to investigate the 159 fires that burned between 1984 and 2012 within 153 watersheds in the western U.S. that had five years of pre-fire and ten years of post-fire water quality and streamflow data (Figure 4; Rust et al. 2018). Data on fire extent and severity, edaphic, climatological, and vegetation recovery characteristics were gathered to identify drivers of water quality response after fire.

We compared water quality responses with the extent of a watershed burned and the combined percent of fire with moderate and high burn severity, conditions that consume nearly all vegetation and surface organic matter (Keeley 2009). The extent burned was calculated from wildfire perimeters overlaid on watershed sampling areas defined by stream gauge locations (Eidenshink et al. 2007; <https://waterdata.usgs.gov/nwis>). Fire severity was estimated with 30 m spatial resolution Landsat imagery and the Differenced Normalized Burn Ratio (DNBR) (Eidenshink et al. 2007); remote burn severity classifications were not validated with on-site measurements. Mean elevation, latitude, slope, and aspect and the distance from the perimeter of each wildfire and the water quality sampling location were estimated from a 30 m digital elevation model (ArcMap 10.1, ESRI, Redlands, CA). We also estimated the distance between water sampling locations and cities with >100,000 people that are potential sources of air pollution and water quality impairment.

Edaphic Variables

Soil properties that influence erosion, nutrient and metal export and post-fire recovery were averaged for each wildfire using publicly available data from the State Soil Geographic Database (STATSGO; Schwarz and Alexander, 1995; Soil Survey Staff). While the STATSGO database contains dozens of edaphic variables, we selected soil properties that are known to affect water quality in streams and are used in watershed classification schemes (Robertson et al. 2006). Field capacity **determines** both plant water stress and soil oxidation-reduction conditions that regulate dissolved metal dynamics. We also included soil organic matter, calcium carbonate content and texture (percent clay and silt). As an index of soil erodibility, we used the adjusted k-factor that considers rock fragments in surface soils that may mitigate erosion (Wischmeier and Smith 1965; Schwarz and Alexander, 1995; Soil Survey Staff).

Commented [AR3]: Just call it Field capacity

Climatological Factors and Plant Recovery

We evaluated climatic indices that may influence post-fire vegetation recovery. An aridity index (AI), defined as the ratio of mean annual precipitation to mean annual potential evapotranspiration, allows comparison of climate across the western U.S. (www.cgiar-csi.org). We also calculated solar energy available for vegetation re-growth at each burn area (McCune and Keon, 2002) based on slope, latitude, and aspect as follows:

$$\begin{aligned} \text{SolarRad} = & -1.467 + 1.582 * \cos(\text{latitude}) * \cos(\text{slope}) - \\ & 1.5 * \cos(\text{aspect}) * \sin(\text{slope}) * \sin(\text{latitude}) - \\ & 0.262 * \sin(\text{latitude}) * \sin(\text{slope}) + 0.607 * \sin(\text{aspect}) * \sin(\text{slope}) \end{aligned} \quad (\text{Eq. 1})$$

We used the Normalized Difference Vegetation Index (NDVI), the ratio of the near-infrared (NIR) to visible radiances (VIS): $(\text{NIR}-\text{VIS})/(\text{NIR} + \text{VIS})$ as an index of growing season greenness and vegetation recovery (Deering et al. 1975; Prince 1991; Prince and Goward 1995). Data to calculate NDVI before and after each fire were retrieved from the Landsat 5 and Landsat 7 satellites and processed in Google Earth Engine (USGS Earth Explorer <https://earthexplorer.usgs.gov/>; Google, Inc.). Images with > 30% cloud cover were excluded, and remaining images were processed with a cloud-masking algorithm. The maximum NDVI values during the growing season (May through September) were composited for each pixel in the burn area. Pre-fire baseline conditions were calculated from five years of growing season NDVI. Post-fire NDVI was calculated for discrete time periods (Yr 1, Yr 2, Yrs 3-5; Yrs 6-10).

Statistical Methods

We analyzed individual correlations among predictor variables and streamwater analyte concentrations and flux (R Core Development Team 2010). Statistical independence of each variable and individual correlations between predictor and response variables were tested using Spearman's rank correlation coefficient, or Spearman's rho (r_s), a non-parametric measure of correlation among two variables (Tamhane and Dunlop, 2000). Correlations were compared to a chart of critical values for Spearman's rho, for a two-tailed hypothesis, where correlations were statistically significant if *p-value* (p) < 0.05.

In addition to evaluating individual correlations, we applied a regression tree technique to examine the influence of predictor variables on water quality response. We used a non-parametric conditional inference tree (CI tree) method that does not assume independence among predictor variables or require assumptions of linearity and is effective at identifying predictor variables even where there are complex interactions (Hothorn et al., 2006a; Hothorn et al., 2006b; Quinn and Keough, 2002). The CI tree approach defines thresholds for those predictor variables with the strongest association for a given water quality response variable (Hothorn et al., 2006a; Hothorn et al., 2006b). We used an *a priori* p -value < 0.05 to identify thresholds. The CI tree method uses a chi-square test statistic to test the association between the predictor variable and response variable; the chi-square contingency table requires a sufficient quantity of observations (Das et al. 2009). For our water quality response variables, individual monitoring stations did not all report the same specific cation or metal forms, so we evaluated the post-fire change for aggregates of individual constituents. Others have demonstrated that physical water quality variables such as cations, anions and heavy metals behave similarly and are highly correlated with one another in surface water (Vega et al. 1998; Kazi et al. 2009). Hence, evaluation of cations aggregated calcium, magnesium, potassium, and sodium as response variables, and the evaluation of post-fire change in metals (both dissolved and total) aggregated aluminum, barium, cadmium, copper, lead, manganese and zinc as response variables. Each metal response for each fire is treated as an independent sample as the algorithm searches for the best split points among the predictor variables to partition the decision tree. Total metals refers to the change in total metals concentration or loading, rather than the dissolved portion, of individual metals; while the responses are evaluated together they are not summed together.

3.3 Results and Discussion

Compiling a large dataset allowed a more systematic and expansive investigation of variables that influence post-fire water quality response than previously reported. Furthermore, results of this study illuminate the physical, edaphic, and biological characteristics that mitigate response and accelerate water quality recovery. We observed some broad themes: soil organic matter (SOM), soil textural components, soil water content, fire burn severity, and vegetation recovery influenced the type and magnitude of the water quality responses. Other studies have observed an individual fire's burn severity (Rhoades et al. 2011) and vegetation recovery influence post-fire nutrient concentrations and hydrologic response (Kinoshita and Hogue 2011), our analysis echoes these findings and further reveals the additional influence of a watershed's edaphic characteristics on post-fire water quality response.

Determinants of post-fire stream nitrogen and phosphorus

Soil calcium carbonate was well correlated to the percent post-fire change in nitrate concentration ($r_s = 0.66$, $n = 78$, $p < 0.001$). The percent of the fire that burned at high severity was positively correlated with the percent change in concentration of dissolved organic nitrogen ($r_s = 0.59$, $n = 78$, $p < 0.001$). Total N (TN) concentration and flux increased in 34% of burned watersheds during the first five years after fire, but no single factor was significantly related to these changes. During discrete post-fire periods (Yr 1 and Yrs 6-10) TN flux was positively correlated with the percent of the fire that burned at moderate and high severity ($r_s = 0.53$ and $r_s = 0.56$, $n = 32$, $p < 0.01$).

There were significant correlations between post-fire change in stream TP response and burn severity and watershed characteristics. The proportion of a fire that burned at moderate and high severity was correlated with TP loading rate during all post-fire periods ($r_s = 0.53$ to $r_s = 0.70$, $n = 21$, $p < 0.05$).

Soil properties before the fire and a fire's burn severity drive water quality response. Moderate and high burn severity fires can modify soil properties, increasing runoff and erosion. Burn severity was significantly correlated with post-fire increases in dissolved and total nutrients, base cations and metals entering streams. Higher severity fires commonly increase runoff, erosion, and stream nitrate (Lane et al. 2006; Rhoades et al., 2011). Moody et al. (2013) summarized numerous studies and found that soil properties altered by wildfire are one of the major features that govern post-fire erosion and sediment transport. Our study agrees. Larger (> 20% of the watershed burned) and more severe fires had a greater detectable change in water quality. Specifically, streams with a significant change in the loading rate of total nitrogen and phosphorus were draining basins that had a high proportion of both moderate and high severity fires. This agrees with previous research (Riggan et al., 1994; Ranalli, 2004; Townsend and Douglas, 2004; Arkle et al., 2010; Rhoades et al., 2011).

Determinants of heavy metal response

The CI tree method identified a threshold in post-fire dissolved metal concentration associated with soil organic matter (SOM) content ($p = 0.02$; Figure 7). Where pre-fire SOM exceeded 2%, post-fire dissolved metal concentrations decreased compared to pre-fire conditions. There was no change in dissolved metal concentrations in areas with <2% SOM. Though the median percent

change was zero, the fourth quartile showed some streams with a 100 percent change in concentration; SOM of <2% was correlated with a large positive change in dissolved metal concentrations.

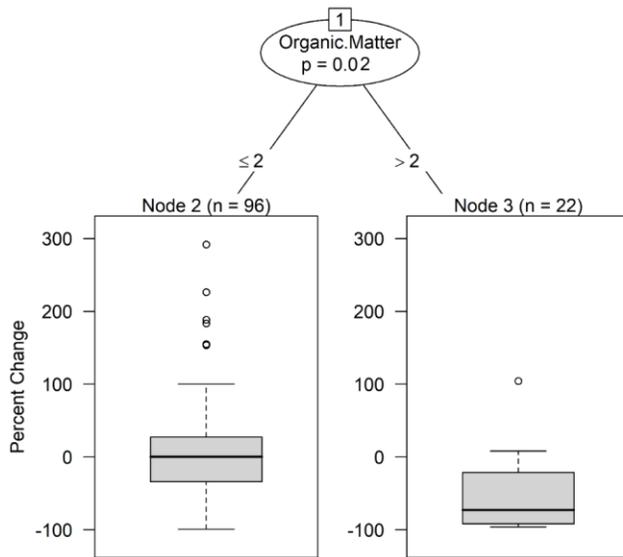


Figure 7. Conditional inference tree results illustrating the significant relationship between the percent of organic matter in the burn area soil and the median percent change in dissolved metals concentration (Al, Ba, Cd, Cu, Mn, Pb, and Zn) five years after fire.

Of the broad list of physical, edaphic and biological predictor variables selected in this study, SOM influenced the dissolved metals response. Where greater SOM is present, dissolved metals will bind and form complexes; the metals are no longer in solution and are retained in particulate form and are no longer in dissolved form (Shaw 1989; Weng *et al.*, 2002; Toribio and Romanya, 2006). SOM reduces the mobility of the bioavailable dissolved metals. This could help sensitive aquatic life, high concentrations of aqueous forms of zinc, copper, cadmium and other metals are lethal to rainbow trout (*Oncorhynchus mykiss*) (Hogstrand *et al.* 1994), a fish that occupies many streams in the western U.S. However, fires combust organic carbon, reducing the available organic matter, which can lead to an even greater increase in both total and dissolved metals (Pinedo-Gonzalez *et al.* 2016).

The CI tree identified drivers of both the change in concentration and loading rate of total metals in the five years after fire. The percent change in total metals concentration was influenced by the vegetation recovery (NDVI) the first year after the fire ($p = 0.01$; Figure 8). When vegetation

recovery was weaker (≤ 0.4) there was a positive increase in the total metal concentrations (node 2). When the vegetation recovery was strong (> 0.4), the amount of solar radiation (node 3) available determined the direction of the total metals response ($p = 0.02$). When the solar radiation available was high (> 0.9), there was no change in the median total metals concentration. Solar radiation was closely related to vegetation growth. When there was high solar radiation, the vegetation recovery was also likely to be high. If the vegetation recovery was weak, and there was less solar radiation available (≤ 0.9), there was a negative change in median total metals concentrations.

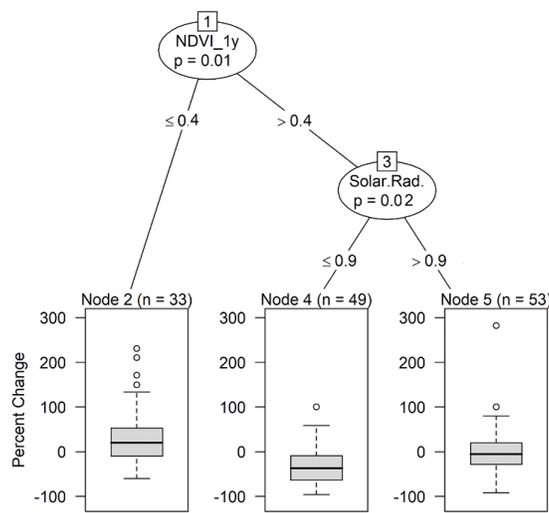


Figure 8. Conditional inference tree results illustrating the significant relationship between the first year vegetation growth (NDVI_1y), solar radiation and the median percent change in total metals concentration (Bo, Cd, Cu, Fe, Mn, Ni, Pb, Se, Zn) five years after fire.

When vegetation recovers, soil properties, such as infiltration depth and erosion rates can recover and even improve (Certini, 2005). We found that post-fire vegetation cover governed post-fire dissolved organic nitrogen concentration, total phosphorus and total metals concentration and flux. Weak post-fire vegetation recovery (< 0.4 NDVI) was associated with higher post-fire total metal concentrations and loading rates.

Post-fire vegetation recovery can be rapid under favorable climate and solar radiation conditions (Wittenberg *et al.* 2007; Wang and Zhang 2017). Vegetation recovery stabilizes soils and increases nutrient demand to limit sediment and nutrient losses to streamwater. Wang and Zhang (2017) observed the understory vegetation recovers quickly, but climax species such as evergreens are slow to return and can take 25-50 years to return after fire. Here we found any type of vegetation recovery (detected as greenness) the first two years after fire influenced the concentration and flux

of dissolved and total nutrients and metals in receiving waters. In this analysis, neither erodibility (k-factor) or slope of burned areas were related to post-fire changes in stream water, though burn severity and post-fire NDVI were.

3.4 Conclusion

Wildfires can cause a wide range of water quality impacts. Identifying determinants of post-fire water quality response, on a broad spatial and temporal scale, as we have done here, facilitates anticipation of water quality impacts following fire.

Overall, the proportion of calcium carbonate and organic matter in the soil, in addition to fire severity and vegetation recovery drive the post-fire water quality response in receiving waters. When a larger proportion of organic matter is present in the soils before the fire, fewer dissolved metals are released into the water. The severity of the fire can influence both the vegetation recovery (as measured in this study with NDVI) and the nutrient concentration and loading in receiving streams. When fires are moderate and high severity, there is an increase in concentration of organic nitrogen, total nitrogen loading, and total phosphorus downstream of the fire. We found that fire severity was negatively correlated with vegetation greenness after the fire, when the vegetation is slow to recover, organic nitrogen and total metal concentrations and flux are higher below the fire. After evaluating almost 30 different physical watershed and fire characteristics, it is evident that the rate of vegetation recovery mitigates water quality change after fire. While this conclusion may be implicit in general assumptions about fire recovery, utilizing a broad dataset provided evidence to validate this assumption.

4.0 Concluding Remarks and Key Findings

The objective of this research was to better understand how wildfires impact water quality and aquatic ecosystems in receiving streams. The aim was to increase knowledge of wildfire's effects by identifying fire's general impacts on water quality and determine the watershed features that govern recovery. This work also sought to improve understanding of the duration of wildfire's impacts and the corresponding recovery of the ecosystem.

Overall the research compiled in this final report highlights the complex nature of wildfire impacts on water quality. Utilizing a broader dataset, including both abiotic and biotic changes from fire, it was possible to evaluate the ecosystem as a whole. The insect and fish populations showed dramatic impairment and recovery. If we had only examined water quality, we would have missed the biotic recovery that was occurring despite the continued water quality impairment from high turbidity. Broadening the spatial scale through looking at multiple fires exposed common responses in water quality. Compiling the physical and climatological characteristics of all fire impacted watersheds provided the chance to discover the key factors driving water quality response. Land and water managers in areas prone to wildfire can use these broader-scale results

to anticipate changes in water quality after the next fire. Identifying general water quality responses and the key watershed and climatological characteristics that control them provides the opportunity to optimize the potential for recovery.

The watershed scale properties collected for this analysis interact in complex ways. We tried to formulate a regression equation to explain how different watershed characteristics influence the water quality response after fire, but found it is not as simple as a linear equation. Principle component analysis was also utilized to identify important combinations of variables that drive the water quality response. However, in the end, due to the complex interactions and broad scale of the study, the conditional inference tree provided the best method of identifying key determinants of post-fire water quality response.

The soil properties of the watershed before the fire and the severity of the fire itself are the primary drivers of the immediate (< 5 year) water quality response. While vegetation recovery, of any kind measured here with NDVI as an indicator of greenness, mitigates the water quality impacts from fire and facilitates water quality recovery. In climates where vegetation recovers quickly, soils are stabilized, erosion is reduced, and less total and dissolved nutrients and metals are delivered to the receiving streams.

This was a broad watershed scale study. In our analysis of 159 fires in the western U.S., the extent of the watershed burned did not influence the water quality response. Because we relied on public data, collected years before a fire occurred, many of the water quality sampling sites were several kilometers downstream of the burn scar. The watersheds were large, much larger than fire studies conducted in the field immediately following a fire, where the sampling locations and watershed outlet points are selected in close proximity to the burn scar. Here, many of the watersheds in the study are large and have less than 10% of the total area burned. Yet a significant water quality impact was still detectable over the first five years after the fire in some of the watersheds. Unlike what other studies have found, where the extent of the watershed burned determined the degree of the water quality impact, our study found that regardless of the proportion of watershed burned, a water quality impact can still occur.

4.1 Implications for Management and Future Research

Our understanding of the impacts that fire has on water quality is not complete, testing our conditional inference tree models in regions outside of the western US would further inform our empirical models. Research to further understand mechanisms of wildfire recovery, specifically vegetation and macroinvertebrate recovery, are necessary. Soil characteristics, burn severity, and vegetation recovery should be considered relevant parameters in any post-fire water quality modeling effort.

This research also revealed the value of publicly shared data. In the future, building on the data already collected in the fire-water quality database will help managers to ask and answer even more questions related to post-fire water quality. Data on dissolved and total metals concentrations were limited, and agencies should be encouraged to conduct more regular water quality monitoring, including metals data. Ideally physical and chemical water quality characteristics would be monitored monthly and data would be shared online. Through the use of remote sensing and other available data tools, it was possible to characterize a large number of fire-impacted watersheds. The water quality data, or response variable in our studies, was more difficult to acquire. With more data available, even more trends in post-fire water quality would be exposed. Understanding the degree and duration of water quality impacts from fire will help support land and water resource managers as they face expanding wildfires and their impacts in the western U.S.

References

- Abatzoglou, JT and Williams, AP (2016) Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences* **113**, 11770–11775. doi:10.1073/pnas.1607171113
- Arkle, R. S., Pilliod, D. S. and Strickler, K. (2010). Fire, flow and dynamic equilibrium in stream macroinvertebrate communities. *Freshwater Biology* **55**, 299–314.
- Belillas, CM and Rodà, F (1993) The effects of fire on water quality, dissolved nutrient losses and the export of particulate matter from dry heathland catchments. *Journal of Hydrology* **150**, 1–17.
- Bilotta, G. S. and R.E. Brazier. 2008. Understanding the influence of suspended solids on water quality and aquatic biota. *Water Research* **42**, 2849–2861. doi:10/1016/j.watres.2008.03.018
- Bladon, KD, Emelko, MB, Silins, U and Stone, M (2014) Wildfire and the future of water supply. *Environmental science & technology* **48**, 8936–8943. doi:10.1021/es500130g
- Bladon, KD, Silins, U, Wagner, MJ, and Stone, M (2008) Wildfire impacts on nitrogen concentration and production from headwater streams in southern Alberta's Rocky Mountains. *Canadian journal of forestry research* **38**, 2859–2371. doi:10.1139/X08-071
- Buchanan, T.J., and Somers, W.P. (1969) Discharge measurements at gaging stations: U.S. Geological Survey Techniques of Water-Resources Investigations, book 3, chap A8, p. 65 (<https://pubs.usgs.gov/twri/twri3a8/>)
- Burke, JM, Prepas, EE and Pinder, S (2005) Runoff and phosphorus export patterns in large forested watersheds on the western Canadian Boreal Plain before and for 4 years after wildfire. *Journal of Environmental Engineering and Science* **4**, 319–325. doi:10.1139/S04-072
- Burke, M. P., Hogue, T.S., Kinoshita, A.M., Barco, J., Wessel, C., Stein, E.D. (2013). Pre-and post-fire pollutant loads in an urban fringe watershed in Southern California. *Environmental monitoring and assessment* **185**, 10131–10145. doi:10.1007/s10661-013-3318-9
- Burton, C.A., Hoefen, TM, Plumlee, GS, Baumberger, KL, Backlin, AR, Gallegos, E, Fisher, RN (2016) Trace Elements in Stormflow, Ash, and Burned Soil following the 2009 Station Fire in Southern California. *PloS one* **11**, e0153372. doi: 10.1371/journal.pone.0153372
- Burton, T. A. (2005). Fish and stream habitat risks from uncharacteristic wildfire: observations from 17 years of fire-related disturbances on the Boise National Forest, Idaho. *Forest Ecology and Management* **211**, 140–149. doi: 10.1016/j.foreco.2005.02.063
- Certini, G. (2005). Effects of fire on properties of forest soils: a review. *Oecologia* **143**, 1–10.

Chambers, ME, Fornwalt, PJ, Malone, SL and Battaglia, MA (2016) Patterns of conifer regeneration following high severity wildfire in ponderosa pine – dominated forests of the Colorado Front Range. *Forest Ecology and Management* **378**, 57–67. doi: 10.1016/j.foreco.2016.07.001

Colorado Department of Public Health and Environment (2010). Policy 10-1, Aquatic Life Use Attainment, Methodology to determine use attainment for rivers and streams, Appendix D, Methodology for determining biological condition.

Colorado Wildlife Commission Policy. Wild and Gold Medal Trout Management. 2008

Dahm, C. N., Candelaria-Ley, R. I., Reale, C. S., Reale, J. K. and Van Horn, D. J. (2015). Extreme water quality degradation following a catastrophic forest fire. *Freshwater Biology* **60**, 2584–2599. doi: 10.1111/fwb.12548

Das, A, Abdel-Aty, M and Pande, A (2009) Using conditional inference forests to identify the factors affecting crash severity on arterial corridors. *Journal of Safety Research* **40**, 317–327. doi:10.1016/j.jsr.2009.05.003.

Deering, D. W., Rouse, J.W., Haas, R.H., and Schall, J.A. (1975). Measuring forage production of grazing units from Landsat MSS data. *Proceedings of 10th international symposium on remote sensing of environment, 1975*. ERIM

DeBano, LF (2000) The role of fire and soil heating on water repellency in wildland environments: a review. *Journal of Hydrology* **231**, 195–206.

Earl, SR and Blinn, DW (2003) Effects of wildfire ash on water chemistry and biota in South-Western USA streams. *Freshwater Biology* **48**, 1015–1030.

Eidenshink, J., Schwind, B., Brewerm, K., Zhu, Z., Quayle, B., Howard, S. (2007). A project for monitoring trends in burn severity. *Fire Ecology Special Issue* 3.

Emelko, MB, Silins, U, Bladon, KD and Stone, M (2011) Implications of land disturbance on drinking water treatability in a changing climate: demonstrating the need for ‘source water supply and protection’ strategies. *Water Research* **45**, 461–472. doi:10.1016/j.watres.2010.08.051

Emelko, MB, Stone, M, Silins, U, Allin, D, Collins, AL, Williams, CHS, Martens, AM, and Bladon, KD (2015) Sediment-phosphorus dynamics can shift aquatic ecology and cause downstream legacy effects after wildfire in large river systems. *Global change biology*. doi: 10.1111/gcb.13073

Falcone, J. (2011) GAGES-II: Geospatial attributes of gages for evaluating streamflow. U.S. Geological Survey, Reston, Virginia.

(https://water.usgs.gov/lookup/geospatial?gagesII_Sept2011)

Google, Inc. Google Earth Engine. Accessed 2017.

Gurarie, E, Andrews, RD and Laidre, KL (2009) A novel method for identifying behavioural changes in animal movement data. *Ecology Letters* **12**, 395–408. doi:10.1111/j.1461-0248.2009.01293

Harvey, BJ (2016) Human-caused climate change is now a key driver of forest fire activity in the western United States. *Publication of National Academy of Sciences*. doi:10.1073/pnas.1612926113

Helsel, D. R. and Hirsch, R. M. *Statistical methods in water resources*. **49**, (Elsevier, 1992).

Hogstrand, C, Wilson, RW, Polger, D and Wood, CM (1994) Effects of zinc on the kinetics of branchial calcium uptake in freshwater rainbow trout during adaptation to waterborne zinc. *Journal of Experimental Biology* **186**: 55-73.

Hothorn, T., Hornik, K., Zeileis, A. (2006a). Party: a laboratory for recursive Partytioning. R Package Version 0.9-0 (<http://CRAN.R-project.org>).

Hothorn, T., Hornik, K., Zeileis, A. (2006b) Unbiased recursive partitioning: a conditional inference framework. *Journal of Computational and Graphical Statistics*, **15**(3), 651-674

Howell, P.J. (2001) Effects of disturbance and management of forest health on fish and fish habitat in Eastern Oregon and Washington, *Northwest Science* **75**, 157-166

Kazi, TG, Arain, MB, Jamali, MK, Jalbani, N, Afridi, HI, Sarfraz, RA, Baig, JA, Shah, AQ (2009) Assessment of water quality of polluted lake using multivariate statistical techniques: A case study. *Ecotoxicology and Environmental Safety* **72**, 301–309. Doi.org/10.1016/j.ecoenv.2008.02.024

Keeley, JE (2009) Fire intensity, fire severity and burn severity: a brief review and suggested usage. *International Journal of Wildland Fire* **18**, 116-126. doi:10.1071/WF07049

Kinoshita, AM and Hogue, TS (2011) Spatial and temporal controls on post-fire hydrologic recovery in Southern California watersheds. *Catena* **87**, 240–252. doi: 10.1016/j.catena.2011.06.005

Kinoshita AM, and Hogue TS (2015) Increased Dry Season Water Yield in Burned Watersheds in Southern California, *Environmental Research Letters*, **10** 014003, doi:10.1088/1748-9326/10/1/014003

Lane, P. N., Sheridan, G. J. and Noske, P. J. (2006) Changes in sediment loads and discharge from small mountain catchments following wildfire in south eastern Australia. *Journal of Hydrology* **331**, 495–510. doi: 10.1016/j.hydrol.2006.05.035

MacArthur, R. H. (1965) Patterns of species diversity. *Biological Reviews* **40**, 510-533. Doi: 10.1111/j.1469-185x.1965.tb00815.x

Mann HB and Whitney DR (1947) On a test of whether one of two random variables is stochastically larger than the other. *The annals of mathematical statistics* 50–60. Institute of Mathematical Statistics.

Mast MA and Clow, DW (2008) Effects of 2003 wildfires on stream chemistry in Glacier National Park, Montana. *Hydrological Processes* **22**, 5013–5023. doi: 10.1002/hyp.7121
McCune, B. and Keon, D. (2002) Equations for potential annual direct incident radiation and heat load. *Journal of Vegetation Science* **13**(4), 603-606.

McCune, B and Keon, D (2002) Equations for potential annual direct incident radiation and heat load. *Journal of Vegetation Science* **13**(4), 603-606.

McKenzie D, Gedalof Z, Peterson DL, and Mote P (2004) Climatic change, wildfire, and conservation. *Conservation Biology* **18**, 890-902.

McKenzie D and Littell JS (2016) Climate change and the eco-hydrology of fire: will area burned increase in a warming western US? *Ecological Applications*. doi: 10.1002/eap.1420

Miller JD, Safford HD, Crimmins M and Thode AE (2009) Quantitative evidence for increasing forest fire severity in the Sierra Nevada and southern Cascade Mountains, California and Nevada, USA. *Ecosystems* **12**, 16–32. doi: 10.1007/s10021-008-9201-9

Minshall, G. W., Brock, J. T. & Varley, J. D. (1989). Wildfires and Yellowstone's stream ecosystems. *BioScience* **39**, 707–715.

Minshall GW (2003) Responses of stream benthic macroinvertebrates to fire. *Forest Ecology and Management* **178**, 155–161. doi: 10.1016/S0378-1127(03)00059-8

Moody, J. A., Shakesby, R. A., Robichaud, P. R., Cannon, S. H. and Martin, D. A. (2013) Current research issues related to post-wildfire runoff and erosion processes. *Earth-Science Reviews* **122**, 10–37.

Morgan P, Heyerdahl EK and Gibson CE (2008) Multi-season climate synchronized forest fires throughout the 20th century, northern Rockies, USA. *Ecology* **89**, 717–728.

Murphy, S. F., McCleskey, R. B. and Writer, J. H. (2012). Effects of flow regime on stream turbidity and suspended solids after wildfire, Colorado Front Range. in *Wildfire and water quality—Processes, impacts, and challenges, Conference in Banff, Canada* 51–58.

National Interagency Coordination Center, Incident Management Situation Report. (9/27/2017) www.nifc.gov/nicc/sitreprt.pdf

Noske PJ, Lane PNJ, and Sheridan GJ (2010) Stream exports of coarse matter and phosphorus following wildfire in NE Victoria, Australia. *Hydrological Processes* **24**, 1514-1529. doi: 10.1002/hyp.7616

Nunes, JP, Doerr, SH, Sheridan, G, Neris, J, Santin, C, Emelko, MB, Silins, U, Robichaud, PR, Elliot, WJ, Keizer, J (2018) Assessing water contamination risk from vegetation fires: Challenges, opportunities and a framework for progress. *Hydrological Processes*. doi:10.1002/hyp.11434

Pechony, O., & Shindell, D. T. (2010). Driving forces of global wildfires over the past millennium and the forthcoming century. *Proceedings of the National Academy of Sciences*, *107*(45), 19167–19170.

Pinedo-Gonzalez P, Hellige B, West AJ and Sañudo-Wilhelmy SA (2016) Changes in the size partitioning of metals in storm runoff following wildfires: Implications for the transport of bioactive trace metals. *Applied Geochemistry*. doi: 10.1016/j.apgeochem.2016.07.016

Prince, S.D. (1991) Satellite remote sensing of primary production comparison of results for Sahelian grassland 1981-1988. *International Journal of Remote Sensing*, **12**, 1301-1312. DOI.10.1080/01431169108929727

PRISM Climate Group, Oregon State University, <http://prism.oregonstate.edu>, created May 10, 2017.

Quinn, G. P., and Keough, M.J. (2002) *Experimental design and data analysis for biologists*. Cambridge University Press.

Ranalli, A. J. *A summary of the scientific literature on the effects of fire on the concentration of nutrients in surface waters*. (DTIC Document, 2004).

Rhoades CC, Entwistle D, and Butler D (2011) The influence of wildfire extent and severity on streamwater chemistry, sediment and temperature following the Hayman Fire, Colorado. *International Journal of Wildland Fire* **20**, 430-442. doi: 10.1071/WF09086

Riggan PJ, Lockwood RN, Jacks PM, Colver CG, Weirich F, DeBano LF, Brass JA (1994) Effects of fire severity on nitrate mobilization in watersheds subject to chronic atmospheric deposition. *Environmental science & technology* **28**, 369–375.

Robertson, DM, Saad, DA and Heisey, DM (2006) A regional classification scheme for estimating reference water quality in streams using land-use-adjusted spatial regression-tree analysis. *Environmental Management* **37**, 209–229. doi:10.1007/s00267-005-0022-8

Rowe, M., D. Essig, and B. Jessup. 2003. Guide to selection of sediment targets for use in Idaho TMDLs

Runge J and Mann J (2008) State of the industry report 2008: charting the course ahead. *AWWA Journal* **10**, 61-74.

Running, S. W. (2006) Is global warming causing more, larger wildfires? *SCIENCE-NEW YORK THEN WASHINGTON*- **313**, 927

Rust, AJ, Hogue, TS, Saxe, S, McCray, J (2018) Post-Fire Water Quality Response in the Western United States. *International Journal of Wildland Fire*. doi.org/10.107/WF17115

Saxe, S, Hogue, TS and Hay, L (2018) Characterization and evaluation of controls on post-fire streamflow response across western US watersheds. *Hydrology and Earth System Sciences* **22**, 1221–1237. doi: 10.5194/hess-22-1221-2018

Schwartz, G.E, and Alexander, R.B. (1995) State Soil Geographic (STATSGO) database for the conterminous United States: U.S. Geological Survey Open-File Report 95-449, <http://water.usgs.gov/lookup/getspatial?ussoils>.

Shaw, E.A., and J.S. Richardson (2001) Direct and indirect effects of sediment pulse duration on stream invertebrate assemblages and rainbow trout (*Oncorhynchus mykiss*) growth and survival. *Canadian Journal of Fisheries and Aquatic Sciences* **58**, 2213-2221.

Silins U, Stone M, Emelko MB and Bladon KD (2009) Sediment production following severe wildfire and post-fire salvage logging in the Rocky Mountain headwaters of the Oldman River Basin, Alberta. *Catena* **79**, 189–197. doi: 10.1016/j.catena.2009.04.001

Smith HG, Sheridan GJ, Lane PNJ, Nyman P and Haydon S (2011) Wildfire effects on water quality in forest catchments: A review with implications for water supply. *Journal of Hydrology* **396**, 170–192. doi: 10.1016/j.jhydrol.2010.10.043

Spracklen DV, Mickley LJ, Logan JA, Hudman RC, Yevich R, Flannigan MD, and Westerling AL (2009) Impacts of climate change from 2000 to 2050 on wildfire activity and carbonaceous aerosol concentrations in the western United States. *Journal of Geophysical Research: Atmospheres* **114**. doi: 10.1029/2008JDO10966

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Web Soil Survey. Available online at <http://websoilsurvey.nrcs.usda.gov/>. Accessed [02/10/2017].

Stevens-Rumann, CS, Kemp, KB, Higuera, PE, Harvey, BJ, Rother, MT, Donato, DC, Morgan, P, Veblen, TT (2018) Evidence for declining forest resilience to wildfires under climate change. *Ecology Letters*, **21**(2), 243–252. doi.org/10.1111/ele.12889

Tamhane, A.C. and Dunlop, D.D. (2002) *Statistics and Data Analysis*. New Jersey: Prentice Hall, Inc.

Taylor WA (2000) Change-point analysis: a powerful new tool for detecting changes. <http://www.variation.com/cpa/tech/changepoint.html>

Townsend, S.A., Douglas, M.M. (2004) The effect of wildfire on stream water quality and catchment water yield in a tropical savanna excluded from fire for 10 years (Kakadu National park, North Australia). *Water Resources* **38**, 30513058

United States Department of Agriculture-Forest Service Burned Area Report. FSH 2509.13. July 2013

United States Environmental Protection Agency, Environmental Sciences Section (1993). ESS Method 340.2, Total suspended solids, mass balance, (3) chapter 2.

United States Environmental Protection Agency (1979) Methods for the chemical analysis of water and wastes, EPA 600/4-79-020.

United States Department of the Interior, U.S. Environmental Protection Agency, Storage and retrieval and water quality exchange (<https://www.epa.gov/waterdata/storage-and-retrieval-and-water-quality-exchange>).

United States Department of the Interior, U.S. Geological Survey. USGS Water Data for USA (<https://waterdata.usgs.gov/nwis>).

Vega, M, Pardo, R, Barrado, E, and Debán, L (1998) Assessment of seasonal and polluting effects on the quality of river water by exploratory data analysis. *Water Research*, **32**(12), 3581–3592. doi.org/10.1016/S0043-1354(98)00138-9

Verkaik, I., M. Vila-Escalé, M. Rieradevall, C.V. Baxter, P.S. Lake, G.W. Minshall, P. Reich, and N. Prat (2015) Stream macroinvertebrate community responses to fire: are they the same in different fire-prone biogeographic regions? *Freshwater Science* **34**, 1527–1541. doi:10.1086/683370

Wang, J and Zhang, X (2017) Impacts of wildfires on interannual trends in land surface phenology: an investigation of the Hayman Fire. *Environmental Research Letters* **12**, 054008. doi: 10.1088/1748-9326/aa6ad9

Westerling AL, Hidalgo H.G., Cayan D.R. and Swetnam T.W. (2006) Warming and earlier spring increase western US forest wildfire activity. *science* **313**, 940–943. doi: 10.1126/science.1128834

Westerling AL, Turner MG, Smithwick EA, Romme WH and Ryan MG (2011) Continued warming could transform Greater Yellowstone fire regimes by mid-21st century. *Proceedings of the National Academy of Sciences* **108**, 13165–13170. doi: 10.1073/pnas.1110199108

Wischmeier, WH and Smith, DD (1965) Predicting rainfall-erosion losses from cropland east of the Rocky Mountains. Guide for selection of practices for soil and water conservation. *Agricultural Handbook*, **282**. US Gov. Print Office, Washington DC

Wittenberg, L, Malkinson, D, Beerli, O, Halutzky, A, and Tesler, N (2007) Spatial and temporal patterns of vegetation recovery following sequences of forest fires in a Mediterranean landscape, Mt. Carmel Israel. *Catena* **71**, 76-83. doi.org/10.1016/j.catena.2006.10.007.

Writer, J. H., McCleskey, R. B. and Murphy, S. F.(2012). Effects of wildfire on source-water quality and aquatic ecosystems, Colorado Front Range. *Proceedings, Wildfire and Water Quality: Processes, Impacts and Challenges, Banff, Canada*.

APPENDIX A

CONTACT INFORMATION FOR KEY PROJECT PERSONNEL

Terri S. Hogue
Professor and Department Head
Civil and Environmental Engineering
Coolbaugh 206
Colorado School of Mines
Golden, CO 80401
<https://cee.mines.edu>
thogue@mines.edu

John McCray
Professor
Civil and Environmental Engineering
Coolbaugh 206
Colorado School of Mines
Golden, CO 80401
jmccray@mines.edu

Ashley Rust
Post-doctoral researcher
Civil and Environmental Engineering
Coolbaugh 206
Colorado School of Mines
Golden, CO 80401
arust@mymail.mines.edu

APPENDIX B

LIST OF COMPLETED PUBLICATIONS

Publications

Characterization and Evaluation of Controls on Post-Fire Streamflow Response Across Western U.S. Watersheds (2018). Saxe, S., T.S. Hogue, L. Hay. *Hydrology and Earth System Sciences*, **22**, 1221-1237. Doi:10.5194/hess-22-1221-2018

Post-fire Water Quality Response in the western United States (2018). Rust, A.J., S. Saxe, T.S. Hogue, J. McCray. *International Journal of Wildland Fire*, **27**. Doi:10.1071/WF17115

Evaluating the Factors Responsible for Post-fire Water Quality Response in Forests of the Western USA. Rust, A.J., S. Saxe, J. McCray, and T.S. Hogue. (*manuscript in preparation*)

Wildfire Impacts on Water Quality, Insect, and Trout Populations in the Upper Rio Grande. Rust, A.J, T.S. Hogue, J. Randell, A. S. Todd. (*manuscript in preparation*)

Conference Presentations

Using the Soil-Water-Assessment-Tool (SWAT) to Predict Water Quality in Streams After Forest Fire. A. J. Rust and T. S. Hogue. International Association of Wildland Fire Annual Conference, Missoula, Montana, May 2018. S19-11.

Post-fire Trends in Water Quality Response in the western United States. A.J. Rust, S. Saxe, T. S. Hogue, J. McCray. Oral presentation European Geophysical Union Annual Meeting, Vienna, Austria, April 2018. EGU 2018-2893.

Post-fire Water Quality Response and Associated Physical Drivers. A.J. Rust, S. Saxe, T.S. Hogue, J. McCray, and C.C. Rhoades. Oral presentation, American Geophysical Union Fall Meeting, New Orleans, Louisiana, December 12, 2017. H23N-07.

Modeling Water Quality after the 1988 Greater Yellowstone Area Fires. A.P. Backsmeier, A.J. Rust, and T.S. Hogue. Poster Presentation September 27, 2016, Geological Society of America Annual Scientific Meeting, Denver, Colorado. Abstract Number 287601.

Water Quality Impacts from the West Fork Complex Fire: Monitoring Ecosystem Health and Impacts on Downstream Communities in the Upper Rio Grande. A.J. Rust, J. Randell, and T.S. Hogue. Presentation September 28, 2016, Geological Society of America Annual Scientific Meeting, Denver, Colorado.

Evaluating Water Quality Response and Controlling Variables for Burned Watersheds in the Western United States. A.J. Rust, S. Saxe, T.S. Hogue, and J.E. McCray. Poster Presentation, American Geophysical Union Fall Meeting, San Francisco, California, December 2016. Poster Number B23A-0556

Post-fire Water Quality in the Western United States: Understanding and Predicting Short and Long-term Response. T.S. Hogue, A.J. Rust, S. Saxe, J. E. McCray. Poster Presentation, American Geophysical Union Fall Meeting, San Francisco, California, December 2016. Poster Number B23A-0554

Water Quality Impacts from the West Fork Complex Fire: Using Real-Time Data to Monitor Ecosystem Health in the Upper Rio Grande. A. Rust, J. Randell, and T.S. Hogue. Presentation November 18, 2015. American Water Resources Association Conference, Denver, Colorado.

Determinants of Post-fire Water Quality in the Western United States. A. Rust, S. Saxe, F. C. Dolan, T. S. Hogue, and J. E. McCray. Poster Presentation, American Geophysical Union Annual Conference, San Francisco, California, December 2016. Abstract Number NH31A-1884.

Wildfire Impacts on Water Quality, Macroinvertebrates, and Trout: An Initial Survey After the West Fork Complex Fire in the Upper Rio Grande. A. Rust, K.R. Knipper, J. Randell, and T.S. Hogue. Poster Presentation, American Geophysical Union Fall Meeting, San Francisco, California, December 2014. Abstract Number 29367.

Wildfire Impacts on Water Quality, Macroinvertebrates, and Trout: An Initial Survey After the West Fork Complex Fire in the Upper Rio Grande. A. Rust, T.S. Hogue, and J. Randell. Presentation at the American Geophysical Union's Colorado State University Hydrology Days, 3/24/15.

Outreach

Produced a Hotspot on the Southern Rockies Fire Science Network website. We worked with Gloria Edwards, with the Southern Rockies Fire Science Network to create a brief presentation of our initial findings from the West Fork Complex Fire. You may view the hotspot from the Southern Rockies Fire Science Network website (www.southernrockiesfirescience.org) or go to the direct link on YouTube (<https://www.youtube.com/watch?v=bSK7Q3TCI8s>).

Presented preliminary results from our West Fork Complex Fire water quality study to the Rio Grande Round Table, which is a Colorado Water Conservation Board appointed commission. Presenting to this commission was an opportunity to report scientific findings to a group of local water resource decision makers and stakeholders. (Alamosa, Colorado, August 2016).

Featured in a newspaper article about our research in the West Fork Complex Fire and our results demonstrating recovery. Pueblo Chieftain, 8/14/16, "Rio Grande River, Post-wildfire concerns diminish, officials feared what might happen after Papoose and West Fork blazes" by Matt Hildner.

Featured in a radio interview by Mike Clifford that aired on 8/25/16 on KRZA radio station in Alamosa/Taos. The interview was focused on wildfire impacts and recovery.

Published a research brief on the West Fork Complex fire impacts and recovery, the brief showcased our preliminary research results. The brief was reported out to the wider community impacted by the West Fork Complex fire and other fires in Colorado. Research brief is attached to this summary.

West Fork Complex Fire Tour- One year later

This was an event organized by the Southern Rockies Wildland Fire Module. We represented the JFSP and presented preliminary results from our water quality monitoring at this event. (Wolf Creek Ski Area, June 19, 2015)

APPENDIX C

METADATA

Forest fire and water quality data used in this analysis is available and has been uploaded to the JFSP final report website. Data sources and descriptions are included in the metadata spreadsheet. Data will also be publicly available upon publication of our final manuscript for this project (Appendix B) through the USGS ScienceBase webpage: <https://www.sciencebase.gov/catalog/> Metadata, water quality data, geophysical data, and fire data will all be available through the USGS ScienceBase portal, search “Drivers of Post-Fire Water Quality Response”.